



# Artificial intelligence in reactor physics: current status and future prospects

Rui-Zhi Zhang<sup>1</sup> · Sheng-Feng Zhu<sup>1</sup> · Kan Wang<sup>2</sup> · Ding She<sup>2</sup> · Jean-Philippe Argaud<sup>3</sup> · Bertrand Bouriquet<sup>4</sup> · Qing Li<sup>5</sup> · He-Lin Gong<sup>6</sup>

Received: 7 December 2024 / Revised: 3 May 2025 / Accepted: 27 May 2025 / Published online: 24 March 2026

© The Author(s), under exclusive licence to China Science Publishing & Media Ltd. (Science Press), Shanghai Institute of Applied Physics, the Chinese Academy of Sciences, Chinese Nuclear Society 2026

## Abstract

Reactor physics is the study of neutron properties, focusing on the use of models to examine the interactions between neutrons and materials in nuclear reactors. Artificial intelligence (AI) has made significant contributions to reactor physics, such as in operational simulations, safety design, real-time monitoring, core management, and maintenance. This paper presents a comprehensive review of AI approaches in reactor physics, especially considering the category of Machine Learning (ML, which we also refer to as AI/ML to recall the AI name we found in articles), with the aim of describing the application scenarios, frontier topics, unsolved challenges, and future research directions. From equation solving and state parameter prediction to nuclear industry applications, this study provides a step-by-step overview of ML methods applied to steady-state, transient, and burnup problems. Most studies have achieved industry-demanded models by enhancing the efficiency of deterministic methods or correcting uncertainty methods, which leads to successful applications. However, research on ML methods in reactor physics is somewhat fragmented, and the ability to generalize models must be strengthened. Progress is still possible, especially in addressing theoretical challenges and enhancing industrial applications, such as building surrogate models and digital twins.

**Keywords** Reactor physics · Artificial intelligence · Machine learning · Neutron governing equations · Fuel burnup · Simulation · Core design · Monitoring

This work was supported by the Natural Science Foundation of Shanghai (No. 23ZR1429300), Innovation Funds of CNNC (Lingchuang Fund, No. CNNC-LCKY-202234), and the National Natural Science Foundation of China (No. U25A20200).

✉ He-Lin Gong  
gonghelin@sjtu.edu.cn

<sup>1</sup> School of Mathematical Sciences, Shanghai Key Laboratory of Pure Mathematics and Mathematical Practice, East China Normal University, Shanghai 200241, China

<sup>2</sup> Department of Engineering Physics, Tsinghua University, Beijing 100084, China

<sup>3</sup> Électricité de France, R&D, 91120 Palaiseau, France

<sup>4</sup> Électricité de France, DQI, 2 rue Ampère, 93206 Saint-Denis, France

<sup>5</sup> Science and Technology on Reactor System Design Technology Laboratory, Nuclear Power Institute of China, Chengdu 610041, China

<sup>6</sup> Paris Elite Institute of Technology, Shanghai Jiao Tong University, Shanghai 200240, China

## 1 Introduction

A nuclear reactor is a device for controlled nuclear reactions, that is, a device that enables a self-sustaining nuclear chain reaction in a controlled manner. Nuclear reactors can be classified into fission and fusion reactors depending on how atomic nuclei produce energy. Currently, fission reactors are the most widely used reactors in practical engineering applications.

Fission reactors have a wide range of applications, with electricity generation being the most common, serving as the core component of nuclear power plants. Typically, a fission reactor consists of nuclear fuel, a coolant, a moderator, a neutron absorber, structural materials, and control mechanisms for regulating the fission process [1].

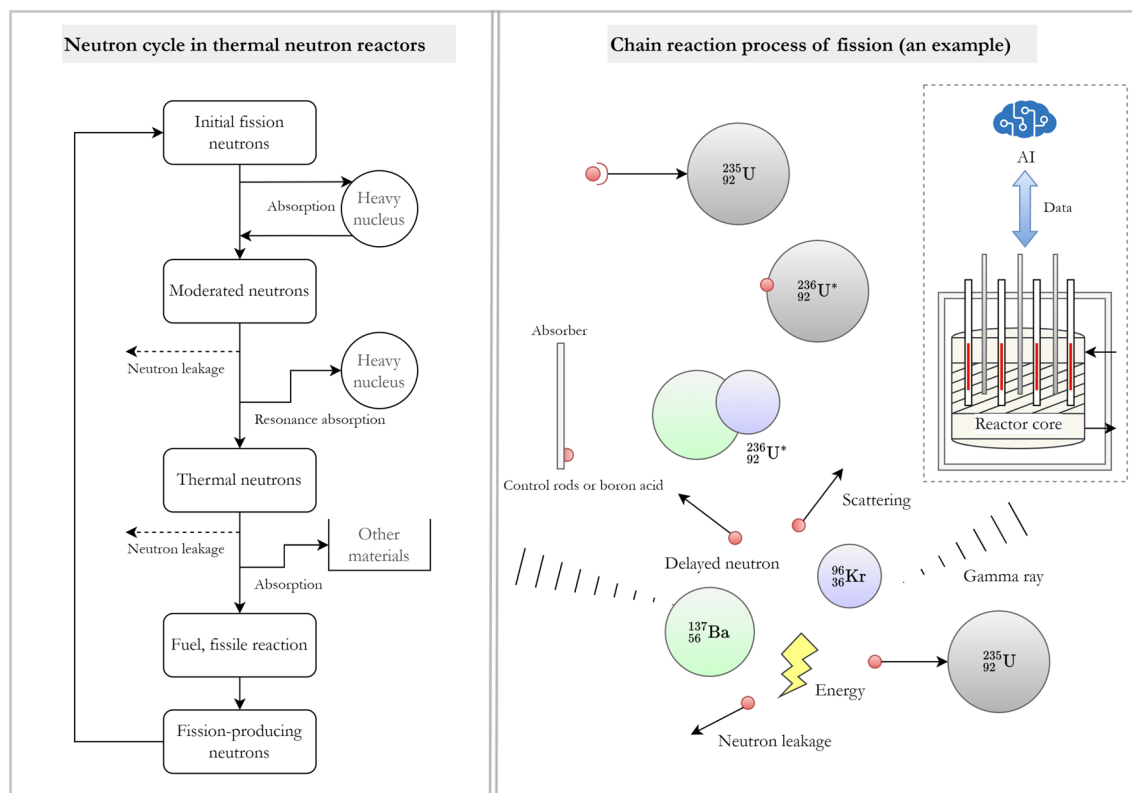
A fission reaction releases energy by splitting a heavy atomic nucleus into two (binary) or three (ternary) fragments [2]. Meanwhile, multiple new neutrons are produced, which can induce further fission reactions, thereby sustaining a

self-sustaining chain reaction. The necessary condition for maintaining this chain reaction is that at least one of the newly created neutrons successfully causes a fission event. However, not all neutrons contribute to further fission; some may be absorbed by non-fissile materials, whereas others may escape from the reactor core. The fission chain reaction is shown in Fig. 1.

In general, there are many types of reactors, including light water reactors (LWRs), heavy water reactors (HWRs), gas-cooled reactors (GCRs), and fast breeder reactors (FBRs) [3]. Among these, LWRs are the most widely used and are further subdivided into boiling water reactors (BWRs) and pressurized water reactors (PWRs) [4]. In the case of LWRs, for example, despite their proven safety and regulatory approval, the high construction costs and long-term operational challenges of large conventional LWRs have driven interest in developing fission reactors with significant improvements over the latest generation of fission reactors. These include LWRs designs that are much smaller than existing reactors and concepts that use different

moderators, coolants, and fuel types [4]. The main types of advanced reactors include advanced water-cooled reactors (WCRs), GCRs, liquid metal-cooled reactors (LMRs), molten salt reactors (MSRs), and fusion reactors. Any research aimed at optimizing reactors requires an analysis of reactor properties or prediction of parameters.

Currently, most of the literature may not directly refer to the study of “reactor physics,” but refers to the terms “neutronics,” “nuclear reactor theory,” or “reactor analysis,” which have almost similar meanings [5], with the commonality that the relevant methods or research ideas are used, or that the physics related to the neutrons of the fission reaction is involved, which is also the method of definition in this review. Frequent research objectives in the literature include the determination of the neutron position in reactor cores, the reaction of neutrons with the surrounding medium, and the study of the spatio-temporal distribution of neutrons, including the improvement of efficiency by ML methods. In addition, the synthesis and organization of literature related to neutronic interactions with matter in nuclear reactors



**Fig. 1** The process of a fission reaction in a nuclear reactor. A neutron interacts with a heavy nucleus (such as  $^{235}\text{U}$  or  $^{239}\text{Pu}$ ), triggering a fission reaction that splits the heavy nucleus into two or more smaller nuclei. This process releases a large amount of energy, mainly in the form of the kinetic energy of the fission fragments, which is then converted into heat. During fission, additional neutrons are emitted, which can be absorbed, scattered, or trigger further fission

events. If each fission-produced neutron successfully induces at least one new fission, the reaction becomes self-sustaining and forms a chain reaction. Control mechanisms within the reactor regulate this process by absorbing excess neutrons to ensure stability. The application of ML methods to reactor physics mainly considers the optimization of the parameters of this process, which are derived from the requirements of nuclear power plants

using AI/ML methods remain fragmented. For numerical simulation techniques in the field of reactor physics, the latest publication [6] classified the studies into six categories: (i) nuclear data processing and resonance calculation models, (ii) cross section homogenization techniques, (iii) steady-state and transient neutron transport methods, (iv) Monte Carlo approaches and applications, (v) nuclear reactor design and analysis, and (vi) methods for sensitivity and uncertainty analysis. Inspired by this research, we investigated the field of reactor physics, collated the works of literature focusing on frontier applications of methods in ML to the field, and demonstrated what reactor physics is, how it can be solved with the help of ML methods to solve problems related to it, and how to enhance and improve the practical efficiency of the methods.

## 1.1 What reactor physics is

A nuclear power plant is a complex system, and the production of nuclear energy must be operated under very high safety standards [7]. Therefore, predicting the distribution of neutrons throughout the reactor is critical and challenging. As one of the main reactants in a nuclear reactor, neutrons interact with various materials in the reactor core.

Reactor physics is the study of neutron properties in a reactor core [8]. It focuses on methods that use analytical and numerical models to study the interaction between neutrons and matter in reactor cores, which is the basis for reactor design and analysis [8]. This method can be used to solve a range of problems in the simulation and regulation of reactor cores in nuclear power plants. Reactor physics models construct high-fidelity datasets using deterministic and indeterministic methods to obtain critical neutron information of reactor cores [8], to realize the process of operation simulation and design of real reactors on computers during operation, and to realize the maintenance of the nuclear power plant system as well as the safety supervision [9]. The ML-based reactor physics model is an extension of the neutron transport model, which aims to provide more accurate or efficient predictions of neutronic behaviors under certain (possibly more complex) material or geometric configurations, where many-query simulations or real-time computations are required for design or optimal operation purposes [10].

In 1956, Weinberg [11] mentioned in his book on nuclear reactor physics that the theory was mainly concerned with the neutron distribution in nuclear reactors and that the central goal of reactor technology was to generate useful work from nuclear reactors. This provided the basis and ideas for subsequent research on nuclear reactor physics. During the same period, more books appeared on the general direction of the goals of reactor physics [12–14]. In 2005, Zin [1] organized the foundations and

advances in nuclear reactor physics and integrated the two main goals of reactor physics. They focused on the design and analytical methods of this period, problems and limitations, and related research to address them, and provided seven mainstream directions for research, which we list as follows [1].

- Derivation of the multi-group transport equations and the multi-group diffusion equations, with representative solution methods thereof.
- Elements of modern (now almost three decades old) diffusion nodal methods.
- Limitations of nodal methods such as transverse integration, flux reconstruction, and analysis of  $\text{UO}_2$ -MOX mixed cores. Homogenization and related issues need to be addressed.
- Description of the analytic function expansion nodal (AFEN) method.
- Ongoing efforts for three-dimensional whole-core heterogeneous transport calculations and acceleration methods.
- Elements of spatial kinetics calculation methods and coupled neutronics and thermal hydraulics transient analysis.
- Identification of future research and development areas in advanced reactors and Generation-IV reactors, in very high-temperature gas reactor (VHTR) cores.

It is worth pointing out that Marguet's book [15] on the challenges facing reactor physics, the recommendations of which are compiled below, could provide some thoughts for our next efforts within the AI framework.

- Resolution of a 3D core with fine deterministic transport, in “one go” killing the two-step procedure.
- Depletion, or kinetic, Monte Carlo calculations applied to exact geometries.
- On-line codes continuously fed by experimental measurements.
- Better operation of the instrumentation of present reactors or future instrumentation.
- New computational schemes substituting the two-group diffusion method with multi-group methods using simplified transport.
- More prevalent multi-physics coupling of specialized codes so that the physical modeling of phenomena becomes consistent, which means not having high-performing physics in one field being associated with too simplistic models in another.
- Adjoint codes with high perturbation orders to finally obtain uncertainties not solely based on the renowned but controversial “engineer's judgment”.

## 1.2 What artificial intelligence methods are in the literature

In recent years, ML methods, particularly neural networks (NNs) and their variants, have significantly contributed to the advancement of nuclear reactor physics (Fig. 2). However, it is crucial to recognize that the application of AI/ML in this field is not limited to NNs alone. Other classical machine learning methods, such as support vector machines (SVM), random forests (RF), and support vector regression (SVR), also play pivotal roles in addressing various challenges in reactor physics.

AI/ML methods have been widely applied in the simulation of nuclear reactor operations, design of reactor core, and real-time monitoring, management, and maintenance of nuclear power plants. Although advanced methods are already used in the industrial applications of nuclear power plants, they still suffer from the problem of mutual constraints of accuracy and time scale. As powerful autonomous learners, the emergence of AI/ML methods, including but not limited to NNs, presents a better solution to these problems.

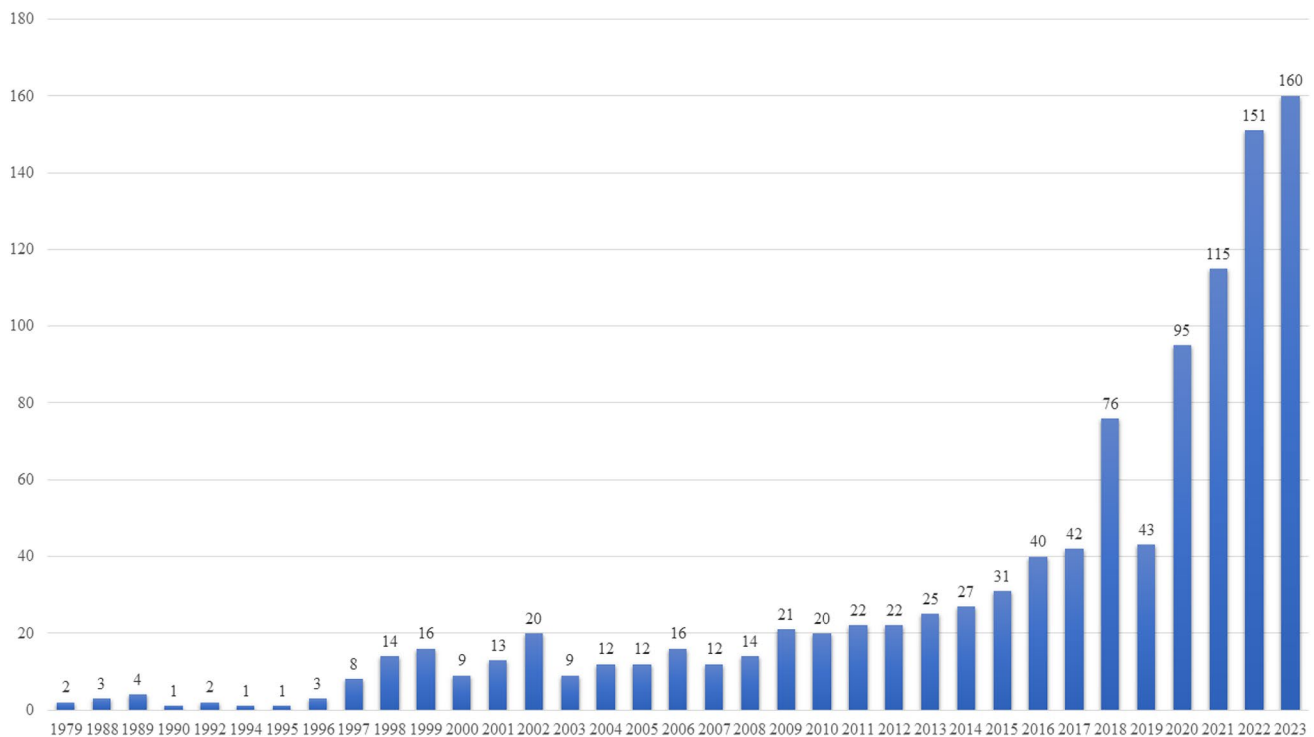
(1) *The comparatively early research on ML in nuclear reactor physics can be traced back to the end of last century.*

These studies involve simple ML methods and focus on the scalar aspects of prediction, such as power and

temperature. The application scenarios are relatively limited, mainly because of the immaturity of computer and neural network technology. The application of ML methods in reactor physics has not been extensively developed. The literature showing relevant typical cases is as follows. Kim et al. [16] investigated the fuel reloading problem in a pressurized water reactor (PWR), that is, the two major constraints of maintaining the local power peaking factor below a predetermined value and maximizing the effective multiplication factor ( $k_{\text{eff}}$ ) for the efficient operation of the reactor. They developed a fast core parameter prediction model based on a backpropagation neural network (BPNN) [16].

(2) *With the recent advances in reactor physics [1], the first decade of the 21st century has a gradual increase in research on the application of ML methods to reactor physics. We list some typical literature from this period.*

Studies have built neural networks to improve this application. Ortiz et al. [17] used neural networks to predict the core parameters of BWR. They further used a polymorphic recurrent neural network (RNN) to optimize the fuel loading pattern of the BWR [18], which was used as the basis for designing a fuel lattice optimization system for the BWR [19]. Kozłowski et al. [20] used Artificial Neural Network (ANN) to develop an innovative approach for the practical application of the Pin-Cell Discontinuity Factors (PDFs).



**Fig. 2** Literature publication trends in reactor physics: This histogram illustrates the annual publication count from the earliest available data through 2023, highlighting a notable surge in research

output since 2020. The horizontal axis denotes the years, and the vertical axis shows the number of publications, offering insights into the growing academic interest in this field

The Support Vector Regression (SVR) method has improved the field of applications. For instance, based on this method, Bae et al. [21] discussed its application in calculating the reactor power peaking factor (PPF), whereas Trontl et al. [22] explored its application in optimizing the reactor loading pattern.

(3) *By the second decade of this century, especially in 2018, the application of ML methods in reactor physics started to gradually explode.*

During this period, with the further development of reactor physics techniques, especially digital simulation techniques, coupled with the maturity of computer technology, the application of ML methods to reactor physics has become progressively more sophisticated and can address more complex application scenarios.

Based on the Hopfield neural network artificial (HNNA), Tayefi et al. [23] designed a new method to guide the heuristic search and distribute the axial variation of enrichment to smoothen the neutron flux. Based on a multilayer perceptron (MLP), Pirouzmand et al. [24] predicted key neutron parameters in the core and constructed a real-time monitoring system. Fernandez et al. [25] evaluated the ability to predict the behavior of a system during accidents with power input and flux loss in the core. Based on cellular neural networks, Starkov et al. [26] constructed a prediction system for the heavy water moderator temperature. Based on the SVR method, Zeng et al. [27] constructed a system performance prediction model consisting of a reactor physical model and a thermo-hydraulic model based on a Transportable Fluoride-salt-cooled High-temperature Reactor (TFHR).

(4) *From 2020 to the present, there is a lot of literature focusing on the application of ML methods to the field of nuclear reactor physics.*

ML techniques, especially neural network techniques, are rapidly developing. There has been a surge in research on ML-based approaches to reactor physics with highly sophisticated application scenarios. Based on a combination of wavelet analysis and convolutional neural networks (CNN), Tagaris et al. [28] proposed a new technique for detecting signal anomalies in nuclear reactors.

The field of prediction of fundamental parameters or phenomena of reactor physics has also advanced. For instance, Bamidele et al. [29] predicted the decay heat of LWR fuel assemblies based on a Gaussian process (GP), support vector machine (SVM) model, and neural network (NN). Berry et al. [30] trained ANN and random forest (RF) classifiers to determine whether the given energy structure enables a multi-group collision probability model to calculate accurate neutron multiplication factors in LWR lattice simulations. Based on a deep neural network (DNN), Chen et al. [31] investigated a linear transport model, whereas Alam et al. [32] developed a multi-stage prediction model. Based on ANN, Dorde et al. [33] studied a Sodium Fast Reactor

(SFR), where the model efficiently evaluated the possible Doppler reactivity of the reactor core over its lifetime range, and Xie et al. [34] solved the neutron diffusion problem for continuous neutron flux distribution. Moreover, Chen et al. [35] screened the burnup state and predicted the neutron parameters in a liquid-fuel MSR using the LightGBM model.

Faced with complex application scenarios, Sobes et al. [36] developed an ML-based algorithm for the design and optimization of a model for the shape of a nuclear reactor core. Turkmen et al. [37] used ML in the single-channel design of an MSR. Digital twin monitoring techniques have also been developed based on application scenarios. Gong et al. [10, 38] proposed a digital twin combining a reduced-order model with data-enabled physics-informed machine learning (ML) to monitor power, where the k-nearest neighbor (KNN) algorithm and decision tree algorithms were used to predict the operating parameters and enable online monitoring of the power distribution. Furthermore, Prantikos et al. [39] improved the digital twin for nuclear reactor monitoring.

Owing to the proposal and development of physics-informed neural network (PINN) techniques, efficient solutions to theoretical problems in reactor physics have been proposed. In 2019, Raissi et al. [40] proposed a PINN, which has been widely used in nuclear reactor physics in the recent past. Using the PINN method, the literature presents learning methods for solving linear transport equations [41], new techniques for the numerical solution of neutron diffusion equations [42], methods for solving point kinetic equations (PKEs) [39], and solving neutron diffusion equations for single- and multi-energy groups [43].

New application scenarios based on reactor physics have given rise to new NN structures, which are a further step up from the simple NN structures of the previous phase. The main focus of this study is the improvement of the PINN algorithm for specific problems and the derivation of many variants. These include deep jointly-informed neural network (DJINN) for the prediction of fission and scattering products [44], conservative PINN (cPINN) for solving heterogeneous neutron diffusion problems with non-smooth solution [45], boundary dependent physics-informed neural network (BDPINN) for solving neutron transport equations [46], and physically informed neural network with migration learning (TL-PINN) for reactor transient prediction [47]. There are also more complex variants and applications. Yang et al. [48] investigated generalized inverse power method neural network (GIPMNN) and physically constrained GIPMNN (PC-GIPMNN) methods to determine eigenvalues. To further improve the accuracy and efficiency, they proposed a data-enabled PINN (DEPINN) [7].

Many types of AI methods have been applied in reactor physics or its related fields, such as KNN, decision tree,



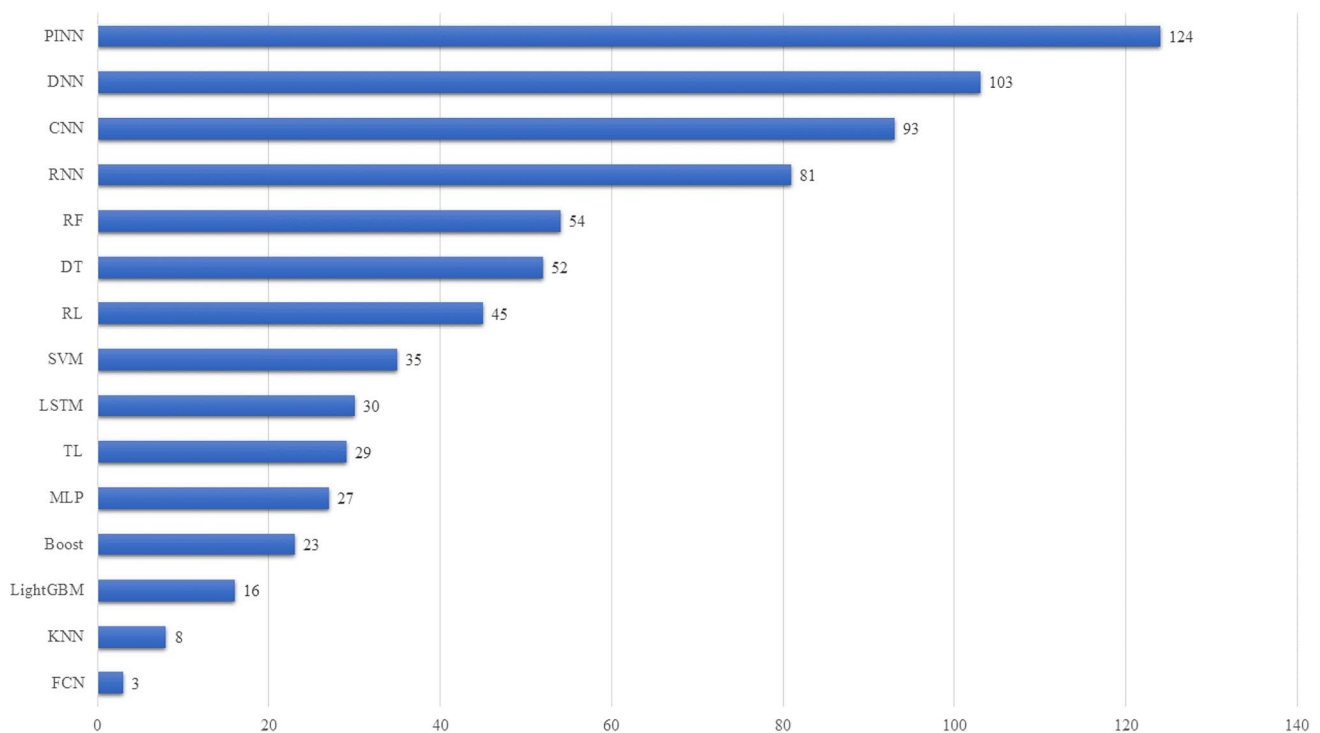
multilayer perceptron (MLP), boosting algorithm, ANN, and PINN [49]. Using the Scopus platform search, we collected the frequency of occurrence of these methods, as shown in Fig. 3.

Current ML methods in reactor physics range from traditional methods, such as integrated learning, to NN-based deep learning, reinforcement learning, and transfer learning. Figure 4 shows the categorization and connections of these methods for easy reading.

In summary, the application of ML methods in the literature related to reactor physics analysis has gone far beyond the basic applications, including reactor core design, simulation, and safety regulation. It involves the mathematical mechanisms behind them, including the solution of the neutron transport equation, neutron diffusion equation, and point kinetic equations, for different scenarios realizing the industrial demands. Higher accuracy in predicting important reactor parameters will contribute to better fuel planning and compliance with technical specifications, whereas increased prediction efficiency will advance the management of nuclear power plants, particularly in the regulation and maintenance of nuclear reactors. Therefore, for the frontiers of reactor physics, the application scenarios are unfolding from steady state to

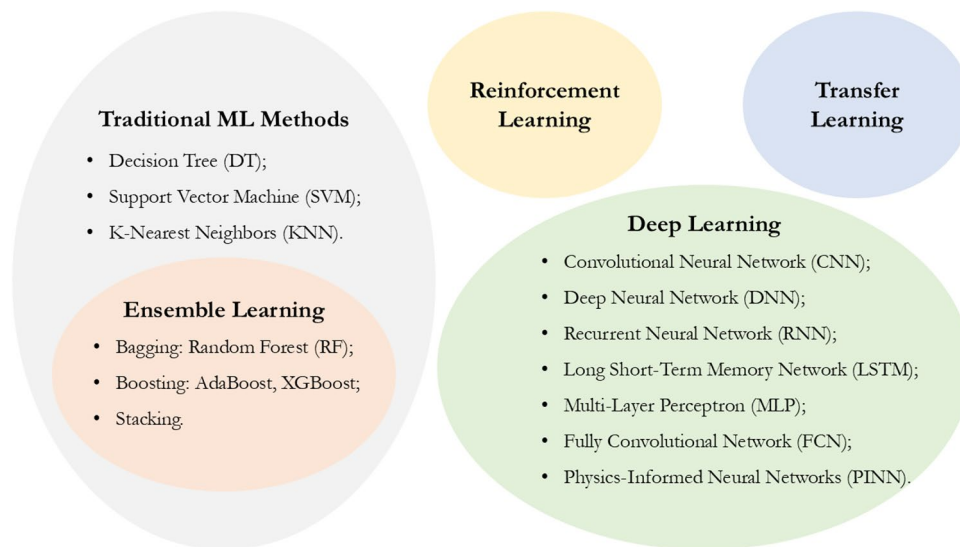
transient, the former of which focuses on core simulation and design, while the latter will necessitate nuclear fuel safety regulation.

The application of ML methods has enabled reactor physics to solve industrial demands at a high rate. The advantages of applying ML to reactor physics are as follows: First, the realization of efficiency gains in simulation and design owing to the ability of ML to learn on its own, which directly improves its ability to adapt to engineering problems. Second, it overcomes the real-time problem in the traditional framework. This is because ML drives research on theories in reactor physics, especially important mathematical theories. The application extends beyond the fission reaction process to encompass all aspects of nuclear reactors, including nuclear data processing [50], thermohydraulics [27, 51], chemical kinetics [52], and radiation transport problems [53]. For example, ML methods can be utilized to calculate wall temperature parameters under certain conditions [54], identify and resolve potential biases in data [55, 56], and data reduction [10, 44]. Furthermore, there are applications for solving problems related to nuclear fusion [57, 58]. Indeed, the development of reactor physics has been unstoppable with the use of ML.



**Fig. 3** Application of AI/ML methods in reactor physics: a comparative analysis. This bar chart categorizes and compares the frequency of various AI/ML methodologies in the literature, including CNN, DNN, RNN, reinforcement learning (RL), transfer learning (TL), long- and short-term memory (LSTM), and fully convolutional net-

works (FCN) within deep learning (DL), as well as the specialized PINN [49] approach. The x-axis lists the ML methods, and the y-axis indicates the corresponding number of publications, reflecting the diverse algorithmic applications in reactor physics research



**Fig. 4** In this paper, we delineate the taxonomy and interplay of ML methods. Traditional methods, particularly those based on ensemble learning, frequently serve as the foundation for predicting core parameters in reactor physics research. Deep learning is the most extensively studied and cutting-edge approach, with numerous methodological variants emerging to address specific challenges in the field. Reinforcement and transfer learning, as burgeoning disciplines,

are poised for further exploration within the reactor physics domain. These areas hold promise for enhancing the efficiency of learning from data and optimizing model transferability to mitigate the time costs associated with training. Future research is likely to delve into these methods, investigating their potential to streamline the predictive capabilities and computational efficiency of reactor physics models

### 1.3 What is this review about

The actual operation of the reactor core is best illustrated by the distribution of power or by the observation of the neutron flux, whereas the multiplication factor directly determines whether the chain reaction is performed [1]. Considering the safety design and optimal operation of a nuclear reactor, it is essential to determine important properties, such as the temperature, neutron flux, reaction rate or power distribution, cross section, and fuel burnup in reactor cores, including both the global state and local details. The analysis of the reactor should involve the determination and prediction of the state of the reactor that sustains the chain reaction by balancing the neutrons from fission and losses from capture and leakage, all based on reactor physics [3]. More specifically, the goal of reactor physics is to determine the neutron multiplication factor for various configurations of a reactor and neutron flux distributions, spatial and temporal, under various operating conditions [1].

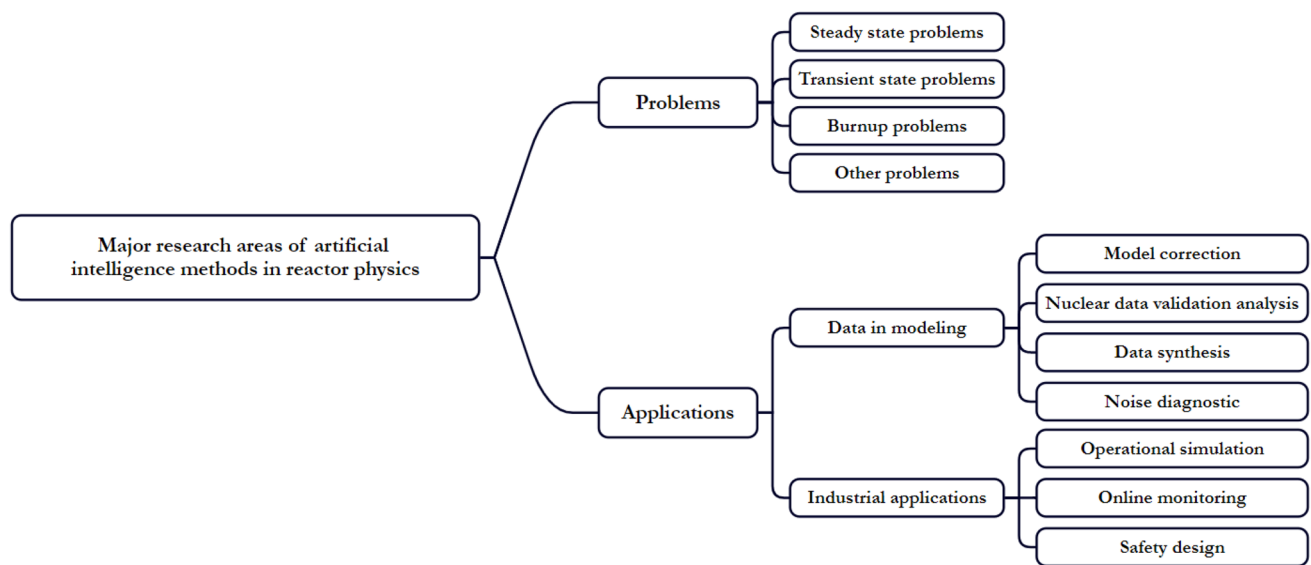
Based on the analysis above, in this survey, we focus on how AI/ML can be used to address different problems in reactor physics, such as solving the neutron transport equation, the building blocks of reactor physics, aspects related to transport theory, the toolset that is already available, future directions and recent trends, as well as issues related to sensitivity and uncertainty analysis. Depending on these problems, we show how high-fidelity nuclear reactor simulations can be customized in the literature through

parameter prediction, data augmentation, and the use of transfer learning.

This review aims to cover most of the frontier ML-related articles related to nuclear reactor physics and learn about advances in machine learning in nuclear physics, as discussed in the review [59]. A practical scenario of the ML approach to reactor physics is shown in Fig. 5. We stress that the objective of this study is not to compare the performance of ML methods, as they were developed for different goals and to address different problems. Thus, this study can serve as a comprehensive guide for navigating the fast-growing ML-related techniques and methodologies in reactor physics. The primary research question is to determine the reactor physics and ML-based applications for the simulation, design, and safety regulation of nuclear reactors. In addition, the review considers research that addresses a broader topic originating from but more than reactor physics, which includes important theories of nuclear reactors, such as thermal hydraulics.

## 2 Fundamentals of reactor physics theory

Theoretical analysis of reactor physics can address issues such as neutron behavior in fission reactors and the interaction of neutrons with individual materials. The governing equations portray neutron transport processes. In the standard description of neutron transport, the neutron flux



**Fig. 5** The mind map shows practical challenges and application scenarios of ML methods in the field of reactor physics. On one hand, this paper takes a cut through some of the challenges that need to be solved urgently in industry, including the steady state and transient problems derived from the neutron spacetime variables, and the burnup problems containing the fuel where the nuclei of the atoms to

be reacted are located, which have been facilitated by ML to achieve good effects; on the other hand, there are several industrial applications based on these problems, including advanced data processing methods, and the practical impetus brought by ML in the operational simulation, online monitoring, and safety design

is related to the position, flight direction, energy, and time of the neutron. The development of traditional numerical methods is mainly driven by the high demands for accuracy and time in industrial simulations.

In multi-scale problems, energy is typically divided into different hierarchical levels. If the neutrons in the reactor core are assumed to have isotropic properties within a specific reaction zone, the directional component of neutron flight can be neglected. This leads to the simplification of the model into two categories: steady-state and transient equations, which are further elaborated in Sect. 3. The steady-state approach focuses on reactor behavior over extended periods, examining the reactor lifetime and final state without considering individual neutron reactions. This removes the correlation between the neutron flux and time, as governed by the neutron diffusion equation. In contrast, transient equations, such as point kinetic equations (PKEs), focus on the time evolution of the system. In this case, the spatial position of individual neutrons is irrelevant; instead, the neutron population and reaction rates are modeled as a function of time, describing the overall kinetics of the reactor rather than the movement of individual neutrons.

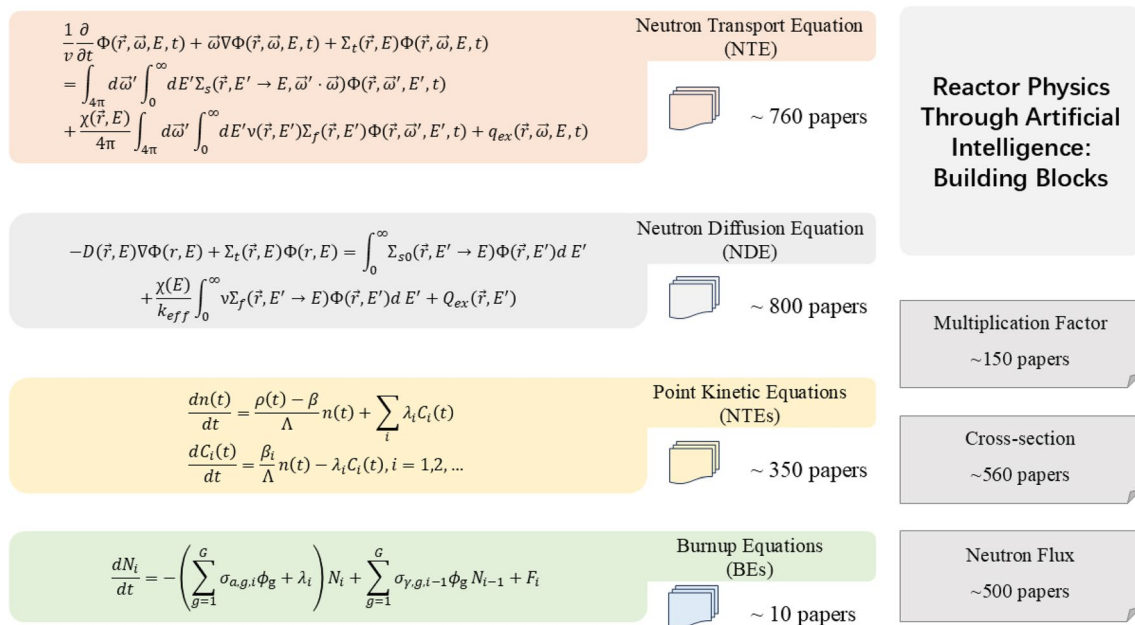
While the previous considerations focused on neutron behavior in the reaction, the material composition of the reactor core also significantly affects the reaction dynamics. Burnup is described by a set of differential equations that model the consumption and production of nuclear fuel, which are commonly referred to as burnup equations.

Burnup is crucial for the study of nuclear reactors, including aspects such as fuel reloading and the power-peaking factor. Proper management of burnup helps ensure neutron flux equilibrium and extends the lifetime of the nuclear reactor. In addition, the burnup distribution plays a crucial role in the analysis of core transients. Specifically, for short-duration transients, the burnup of the core is assumed to be constant, as the depletion process occurs over a much longer time-scale than the duration of transients, which can range from seconds to days.

In particular, since the development of ML technology, data can drive the model. From an engineering perspective, ML approaches can directly predict neutron flux distributions, enhancing reactor simulations without traditional discretization methods or expressed by parameters such as the multiplication factor and reaction cross section. From this perspective, parameter prediction in nuclear reactors has been studied extensively. Some studies have focused directly on power prediction, which is an important parameter in reactor control.

Figure 6 summarizes the fundamental components of reactor physics, distinguishing between the governing equations and key model/engineering parameters. Early research in reactor physics focused on the deterministic approach, that is, the solution process controlled by the four equations mentioned above, which is the first block focused on ML applications in reactor physics. The second segment involves the direct or indirect prediction of important parameters. Their predictions





**Fig. 6** Utilizing search data from the Scopus platform, we conducted a literature review focusing on the foundational elements of reactor physics. Our analysis revealed a significant body of work integrating ML methods to address complex challenges in the field. By examining the core structure of reactor physics, which encompasses the governing equations of nuclear reactions and pivotal state parameters, we

quantified the prevalence of scholarly references in recent years, facilitated by the Scopus platform. There is a discernible surge in research dedicated to the intricate equations governing neutron transport, neutron diffusion, and point kinetics, as well as a pronounced trend toward the study of critical parameters that are essential for reactor physics

go far beyond their value and are more catalysts for solving other problems.

## 2.1 Governing equations

The Boltzmann transport equation [60], which is one of the key equations in nuclear engineering and reactor physics, is commonly used to describe the neutron transport phenomenon. This is an integral-differential equation that describes the neutron flux [61] across the cross section of an oriented plane in an inhomogeneous fissile medium and accurately describes the actual neutron transport process in the medium. Specifically, neutron interactions with the medium during transport, such as scattering and absorption reactions, will occur, and these will affect the neutron flux. Neutron transport equations are based on the principles of conservation of energy and momentum, and by considering these interactions, the behavior of neutrons in a reactor or other medium can be predicted. The Boltzmann transport equation takes the following form

$$\frac{1}{v} \frac{\partial \Phi}{\partial t} + \vec{\omega} \cdot \nabla \Phi + \Sigma_t \Phi = \int_{4\pi} d\vec{\omega}' \int_0^\infty dE' \Sigma_s \Phi' + \frac{\chi}{4\pi} \int_{4\pi} d\vec{\omega}' \int_0^\infty dE' v \Sigma_f \Phi' + q_{ex}. \quad (1)$$

In Eq. (1),  $\Phi(\vec{r}, \vec{\omega}, E, t)$  denotes the neutron flux, which depends on the position vector  $\vec{r}$ , energy  $E$ , and direction of motion  $\vec{\omega}$  at time  $t$ . This flux is a fundamental parameter in nuclear reactor physics because it describes the distribution and intensity of neutrons in the reactor. The term  $\Phi'$  refers to the neutron angular flux at energy  $E'$  and direction  $\vec{\omega}'$ , representing the contributions from neutrons scattering into the specified state  $(\vec{r}, \vec{\omega}, E, t)$  from other energies and directions. The neutron transport equation, in its most general form, involves seven independent variables: Three spatial coordinates in  $\vec{r}$ , two angular coordinates in  $\vec{\omega}$ , energy  $E$ , and time  $t$  [9]. Although this comprehensive model is accurate, it is often simplified in practical reactor designs using approximations such as the diffusion equation.

Equation (1) precisely describes the neutron transport behavior in a medium. More specifically, in the transport process, neutrons interact with the medium and undergo reactions such as scattering and absorption, which affect the neutron flux. In the equation,  $\Sigma$  denotes the macroscopic cross section, that is, the probability that a certain process occurs for a neutron, for example, collision, which includes scattering (either elastic or inelastic scattering), and absorption (either capture, or fission, or others). The other notions are standard.

Neutron transport theory models neutron behavior with greater precision by incorporating angular dependence,

which is particularly important in highly detailed reactor simulations. In contrast, the diffusion approximation simplifies this by assuming an isotropic neutron motion. In contrast, the neutron diffusion equation is a simplification of the neutron transport equation and is commonly used in core calculations for nuclear reactor design and analysis. The theory is considered accurate for relatively homogeneous and large geometries because neutrons tend to move isotropically, that is, without directional preference [13]. The neutron diffusion equation is generally of the following form:

$$-D\nabla^2\Phi + \Sigma_t\Phi = \int_0^\infty \Sigma_{s0}\Phi' dE' + \frac{\chi}{k_{\text{eff}}} \int_0^\infty \nu\Sigma_f\Phi' dE' + Q_{\text{ex}}. \quad (2)$$

Although the neutron diffusion equation has been successfully employed in reactors of various sizes, its application can lead to significant errors owing to the underlying diffusion theory. These errors arise from several factors, including the diffusion approximation itself, spatially integral representations, and simplifications of energy cross section interactions. In particular, regions with large neutron current (flux) gradients, especially near reactor boundaries, can amplify these errors. Such spatial approximations and their associated inaccuracies are well-established features of the method, rather than unforeseen limitations [14, 62]. Several numerical methods can be used to solve these equations, including the finite element methods (FEM), finite volume methods (FVM), and finite difference methods (FDM) [34]. However, the accuracy of these methods is limited by the number of nodes and the geometry of the problem [63].

As the basis of diffusion theory, Fick's law is essentially related to the  $P_1$  approximation of the time-dependent neutron transport equation (the approximation is also known as the neutron telegraph equation), and the diffusion equation further neglects the derivative term of the neutron flux density with respect to time. Because the parabolic nature of the diffusion equation predicts that the particles will have infinite velocities, the particles in the tails of the distribution function will appear at an infinite distance from the source in time  $t = 0+$ ; however, the neutron telegraph equation has finite particle velocities, the value of which is incorrect [62]. Thus, in some sense, it cannot accurately characterize the actual neutron transport process [64].

However, reduced-order models consisting of PKEs have been developed for cases in which the spatial dependence of the neutron flux is negligible [39]. PKEs consist of a system of coupled nonlinear stiff differential equations that model the kinetics of the reactor variables. This is a reduced-order model of the Boltzmann neutron transport equation and the Bateman equation, which describes the 3D spatial and temporal kinetics of a nuclear reactor [47].

The PKEs are derived by neglecting the shape of the neutron flux and neutron density distribution [47].

PKEs, first deduced by Henry [65], reduce the mathematical problem from a system of integral differential equations to a system of ordinary differential equations [66], which allows for the rapid solution of time-dependent neutron transport problems in nuclear reactors. The equation is generally written in 0D and has the following basic form [67].

$$\begin{aligned} \frac{dn}{dt} &= \frac{\rho - \beta}{\Lambda} n + \sum_i \lambda_i C_i, \quad i = 1, 2, \dots \\ \frac{dC_i}{dt} &= \frac{\beta_i}{\Lambda} n - \lambda_i C_i, \quad i = 1, 2, \dots \end{aligned} \quad (3)$$

In Eq. (3),  $n$  stands for the neutron density concentration,  $C_i$  is the delayed neutron precursor density concentration for group  $i$ ,  $\rho$  is the reactivity feedback, which are functions of time  $t$ ,  $\beta_i$  is the delayed neutron fraction for each group, and  $\beta = \sum_i \beta_i$  is the sum of the delayed neutron fractions. In addition,  $\Lambda$  is the mean neutron lifetime in the reactor core, and  $\lambda_i$  is the average decay constant of the  $i$ -th group precursor. Given the appropriate initial conditions, this constitutes a complete set of ordinary differential equations that reflect information about the power level and power fluctuations of a nuclear reactor in a unit of time [67].

In this study, we plan to integrate the extended mainstream ML techniques to solve important governing equations in reactor physics. Table 1 presents a synthesis of the types of AI/ML approaches that have been synthesized in the field of reactor physics, as well as the literature in which the approach has been used.

Recently, with the development of ML technology, the use of ML, especially deep learning (DL), to solve complex differential equations has become a hot research topic in the field of numerical computation [68]. The advantage of resorting to DL instead of traditional neural networks is that it can solve the problem of high computational costs for problems with high-dimensional physical variables and can handle complex boundary conditions [40]. Based on artificial neural networks (ANNs), DL methods have been proposed to solve the neutron diffusion problem for continuous neutron flux distributions without the need for prior regional discretization [34].

In the process of a neutron reaction, the fissile isotopes in the fuel are continuously depleted owing to neutron-induced reactions and radioactive decay, and will also change with the reaction [69]. To accurately calculate the changes in the composition of the fuel during reactor operation, it is necessary to establish a function of the change in each of the isotopes involved in the reaction over time, that is, the burnup equation. The burnup equation is generally written as shown in Eq. (4).

**Table 1** Main ML methods used in the governing equations of the reaction

| NN family | NN type                 | Solving problems                                                                   | Papers                                                                         |
|-----------|-------------------------|------------------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| NN        | Cellular NN             | Spatial and temporal response of the neutron flux distribution                     | Pirouzmand et al. [73]                                                         |
| ANN       | ANN                     | Albedo problem, the Milne problem, and the criticality problem                     | Türeci [76]                                                                    |
| DNN       | DNN                     | Solution of the neutron transport equations                                        | Liu et al. [75]<br>Chen et al. [31]                                            |
| PINN      | PINN                    | Loosely Coupled Reactor Model (LCRM)                                               | Elhareef et al. [77]                                                           |
|           | PINN, DEPINN, GIPMNN    | Solution of neutron diffusion equations<br>Solution of neutron transport equations | Huhn et al. [53],<br>Yang et al. [7],<br>Yang et al. [96],<br>Yang et al. [48] |
|           | PINN                    | Solution of point kinetic equations                                                | Prantikos [39]<br>Schiassi et al. [66]                                         |
|           | Boundary-Dependent PINN | Solution of the neutron transport equations                                        | Xie et al. [46]                                                                |
|           | Conservative PINN       | Heterogeneous seed diffusion problems with non-smooth solutions                    | Wang et al. [45]                                                               |
|           | TL-PINN                 | Reactor transients (RTs) prediction                                                | Konstantinos et al. [47]                                                       |

We provide a synthesis of the literature on the application of machine learning (ML) methods to the governing equations describing neutron behavior in nuclear reactors. Among these, the Physics-Informed Neural Network (PINN) approach has emerged as a particularly prominent technique that has been extensively applied and refined in recent studies. As a deep learning-based framework, PINNs have demonstrated significant efficacy in obtaining numerical solutions to the governing equations, establishing themselves as a robust and innovative tool for advancing reactor physics research

$$\frac{dN_i}{dt} = -\left(\sum_{g=1}^G \sigma_{a,g,i} \Phi_g + \lambda_i\right) N_i + \sum_{g=1}^G \sigma_{\gamma,g,i-1} \Phi_g N_{i-1} + F_i, \quad (4)$$

where  $N_i$  denotes the number of the  $i$ -th nuclide, and  $\sigma_{a,g,i}$  and  $\sigma_{\gamma,g,i}$  denote the absorption and fission cross sections of the  $i$ -th nuclide, respectively. In the formula, the right-hand side contains the disappearance and production of nuclides, respectively, where the first term denotes the disappearance rate of isotope  $i$  due to the absorption of neutrons and decay neutrons, the second term denotes the production rate of isotope  $i$  due to the absorption of neutrons or decay of isotope  $i-1$ , and the third term denotes the production rate due to the fission reaction [70].

It is worth noting that, in general, the neutron angular flux  $\Phi$  is a function of both spatial location  $r$  and time  $t$ , and that there is an interaction between  $N_i$  of the fuel isotope and the neutron angular flux  $\Phi$ . Thus, strictly speaking, Eq. (4) is a nonlinear problem. In practical operations, it is common to divide the core into several burnup regions in which the position does not vary significantly, and thus the variables are independent of  $r$ . Furthermore, given the burnup time step, the neutron flux can be approximated as constant, thus creating a system of ordinary differential equations for each burnup step with respect to time  $t$ .

Among others, convolutional neural networks (CNNs) [71] and deep neural networks (DNNs) [31] have been applied to various problems in reactor physics. However, one of the hottest research topics in deep learning (DL) is the physics-informed neural network (PINN). Unlike traditional data-driven machine learning (ML) methods, which

require large training datasets, PINNs can directly solve higher-order, multi-dimensional equations in a forward manner [68]. The extensive literature on PINNs [41–43, 53] highlights their growing importance in addressing complex physical issues.

Physics-informed neural networks (PINNs) incorporate governing equations (e.g., the neutron diffusion Eq. (2) or the Boltzmann transport Eq. (1)) directly into the neural network loss function. Specifically, the PDE residual and any boundary or initial conditions are enforced during training, allowing the network to learn solutions that inherently respect underlying physics. By leveraging automatic differentiation (AD) to compute derivatives with respect to both the network parameters and input variables, PINNs offer a mesh-free approach that can handle complex reactor geometries and high-dimensional parameter spaces. Variants such as the conservative PINN (cPINN) [45], physically constrained generalized inverse power method neural network (PC-GIPMNN) [48], and boundary-dependent PINN (BDPINN) [46] further extend this framework to address domain decomposition, boundary constraints, and improved training stability. These methods provide a promising pathway for coupling data-driven models with fundamental reactor physics to enhance both the accuracy and computational efficiency.

### 2.1.1 Neutron transport equation

The neutron transport equation delineates the distribution of neutron flux across a cross sectional plane within a heterogeneous fission medium [61]. In principle, this equation

can yield more precise solutions. Nonetheless, the high-fidelity data obtained from solving the transport equation require extensive computational time and substantial computational resources. These limitations often render iterative core design impractical for commercial applications. Conversely, the advantages and disadvantages of grid-based methods are increasingly acknowledged in real-world applications. The accuracy of these methods is fundamentally constrained by the granularity of the grid, quantified by the number of nodes, and the geometric complexity of the problem domain [15,72].

**2.1.1.1 Cellular neural network** Cellular neural networks are an alternative to traditional numerical methods [73]. Based on a cellular neural network, Pirouzmmand et al. [73] simulated the spatio-temporal response of the neutron flux distribution under steady state and transient conditions using the second-order form of the time-dependent neutron transport equation and simulated step perturbations in the core of the reactor. They also invoked the model used on a small pressurized water reactor assembly to simulate the effects of temperature feedback, poisons, and control rods on the neutron flux distribution.

**2.1.1.2 Deep neural network** Chen et al. [31] refer to the traditional  $S_N$  method [74], which discretizes the angle variable of the product of the definite integral term, constructs the approximate discretization of the definite integral term and forms the loss function by Gaussian product group, and gives the results of discrete-time and angle scalar flux density calculation of one-dimensional geometry in the transient case by DNN.

Furthermore, Liu et al. [75] proposed a differential transform order theory for the difficulty of DNN in solving the neutron transport equation with a definite integral term, which first converts the transport equation with a calculus form into a higher-order differential equation, then uses DL based on NN to approximate the original function, and performs a differential downscaling of the original function to obtain the numerical solution of the angular flux density of the transport equation.

**2.1.1.3 Physics-informed neural network** Based on DL frameworks, PINN-based methods also show significant advantages over traditional methods. Huhn et al. [53] solved the stream and interaction terms of the Boltzmann transport equation by PINN, proposed the application of Fourier features and a heuristic-based sampling method to improve the performance of PINN, and verified the advantages of the algorithm in terms of accuracy with the example of a transmission problem in a heterogeneous one-dimensional plate. To eliminate the error caused by the boundary conditions and avoid the curse of dimensionality, Xie et al. [46]

proposed a boundary-dependent physically informed neural network (BDPINN) for solving the neutron transport equation. They also introduced three techniques to improve the BDPINN, including third-order tensor transformation, training set arrangement, and higher-order reconstruction, which optimizes the computational cost and accuracy.

## 2.1.2 Neutron diffusion equation

Solutions derived from the neutron diffusion equation can be extended to a variety of industrial applications, including the simulation and design of nuclear reactors. Advanced reactor simulations often incorporate multi-physics modeling and feature intricate geometries that require more sophisticated analytical capabilities than those provided by conventional grid-based methods.

**2.1.2.1 Artificial neural network** Türeç [76] leveraged established single-velocity neutron transport data with isotropic scattering to address the albedo, Milne, and criticality problems using two distinct ML methods: polynomial regression (PR) and artificial neural networks (ANN). The PR method demonstrated efficacy within the confines of its training data scope, whereas the ANN method, despite requiring more computation time, exhibited robustness beyond the training data limits.

**2.1.2.2 Deep neural network** Dong et al. [42] constructed a DNN as a trial function and substituted it into the neutron diffusion equation to form the residuals, which are used as the weighted loss function of the PINN, so as to approximate the numerical solution of the diffusion equation by deep machine learning. They also proposed techniques such as accelerated convergence methods, efficient parallel search techniques for the proliferation factor, and strategies for learning the inhomogeneous distribution of the sample network points, and analyzed the sensitivity of each key parameter of the neural network.

**2.1.2.3 Physics-informed neural network** Elhareef et al. [77] applied a PINN to solve a loosely coupled reactor model (LCRM) based on the neutron diffusion model. They used a two-dimensional, time-domain independent, constant source diffusion equation to simulate the LCRM problem with zero inflow flux physics conditions, which were reduced to general Robin boundary conditions. Relative to the FEM solution, the PINN obtained an average relative error of approximately 0.63%.

To address the problem of neutron diffusion with heterogeneous neutrons, Xie et al. [34] proposed two mesh-free physical information deep learning (PIDL) methods, including the boundary-dependent method (BDM) and the boundary-independent method (BIM), which provide



continuous symbolic solutions to solve the neutron diffusion problem with a continuous neutron flux distribution. This procedure does not require region discretization and can thus be easily generalized to complex geometries. In tests involving complex geometries and multi-region problems, the BDM method exhibited higher accuracy and flexibility. Research [78] also solved the coupled system of partial differential equations using the PINN method and solved the multi-energy group diffusion problem based on a system of equations consisting of several diffusion equations with neutron fluxes and  $K$  eigenvalues. Wang et al. [45] introduced the concept of cPINN, where PINN is developed for each subdomain and additional conservation laws along the subdomain interfaces are considered, and the method is proven to be effective in solving the heterogeneous neutron diffusion problem with non-smooth solutions. More PINN-related studies are discussed in detail in Sect. 3.

### 2.1.3 Point kinetic equations

The point reactor kinetics (PRK) model is derived from point kinetic equations (PKEs). This model assumes that the flux shape function follows the fundamental mode, which is the solution to the external neutron-source-free balance equation. This approximation remains valid primarily when the system is near criticality, where fission sources dominate the external sources [79].

Compared to traditional numerical methods, the PINN method does not require the time-consuming construction of complex grids and has a short computational time; therefore, it can be applied more efficiently to solve problems in irregular and high-dimensional domains. Considering the advantages of PINN, Prantikos et al. [39] developed a PINN model for solving PKEs and obtained results that were consistently compared to standard numerical methods. Schiassi et al. [66] proposed a new method for solving temperature feedback PKEs based on the PINN method, which is flexible and problem-adaptable. Gatchalian et al. [79] explored the role of the ML method in utilizing measurable quantities from reactor operations and experiments as predictors of  $k_{\text{eff}}$  and kinetic/subcritical parameters.

Transfer learning physics-informed neural network (TL-PINN), the process of pre-training a neural network on data similar to those used for training to enhance performance on a new task, is currently less used in transient reactor physics problems. Konstantinos et al. [47] achieved an improvement in reactor transient (RTs) prediction performance with the help of a TL-PINN method, which reduces the number of model iterations. Specifically, they used a PRK model with six neutron precursor populations, constructed using the experimental parameters of the Purdue University Reactor-1 (PUR-1) research reactor, to generate different reactor RTs with a range of experimentally relevant variables, while the

similarity was characterized using the Hausdorff and Fréchet distances. The model yielded accelerations of up to two orders of magnitude. The average error in the prediction of neutron densities by the conventional PINN and TL-PINN models was less than 1%.

## 2.2 Key reactor parameters

In reactor physics, state parameters are predominantly characterized by the neutron transport equation, its simplified counterpart, the neutron diffusion equation, or the point kinetic equation. These equations can be addressed using both deterministic and probabilistic methods, such as the Monte Carlo method. Regardless of the chosen method, the primary objective is to accurately model the key state parameters within a nuclear reactor. These include the multiplication factor, neutron cross sections, and neutron flux, which are the principal manifestations of the fission reaction, a process that is microscopically intricate and complex. Table 2 provides an overview of the ML techniques employed in the prediction of these parameters, as reported in the literature.

### 2.2.1 Multiplication factor

The multiplication factor, an important quantity in reactor physics, is a measurement of the change in the number of fission neutrons from one neutron generation to the next and is a direct reflection of the ability of a nuclear reactor to maintain conditions for a self-sustaining chain reaction. It is vital to achieve an accurate prediction of the multiplication factor, which determines the critical conditions of the reactor, and accurate values that enable reactor operators to make informed decisions regarding fuel management and overall safety.

The original application of ML methods focused on predicting the multiplication factor, and at the same time, the PPF. Kim et al. [80] developed a fast core parameter prediction system based on a pressurized water reactor (PWR) using back propagation neural networks (BPNs) to model the multiplication factor and the maximum power, which resulted in a large speed improvement with errors within a few percent. Ortiz et al. [19] introduced a method based on a multi-state recurrent neural network to optimize the nuclear fuel lattice system of a BWR to predict the local PPF and the infinite multiplication factor ( $k_{\text{inf}}$ ). Trontl et al. [22] used the support vector regression (SVR) algorithm for the global  $k_{\text{eff}}$  at the cycle begin and end, respectively, as well as the PPF as the target parameter, respectively, to build an ML model and optimize the parameters by genetic algorithms (GA), and obtained a good result with the root mean square error (RMSE) controlled in the order of  $10^{-2}$ .

The application of ML methods in reactor physics is maturing and has achieved better results, particularly in



**Table 2** ML methods for the prediction of state parameters important in the reaction

| State parameters      | ML methods         | Papers                                     |
|-----------------------|--------------------|--------------------------------------------|
| Multiplication factor | ANN, RF            | Berry et al. [30]                          |
|                       | BPN                | Kim et al. [80], Bei et al. [82]           |
|                       | LSTM               | Ren et al. [81]                            |
|                       | Multi-state RNN    | Ortiz et al. [19]                          |
|                       | SVR                | Trontl et al. [22]                         |
| Neutron cross section | DNN, XGBoost       | Oktavian et al. [72], Sun et al. [88]      |
|                       | DNN                | Ravichandran et al. [86]                   |
|                       | Decision tree, KNN | Vicente-Valdez et al. [84], Li et al. [89] |
| Neutron flux          | ANN                | Xie et al. [34]                            |
|                       | CNN                | Berry et al. [93]                          |
|                       | FCN                | Zhang et al. [71]                          |
|                       | HNNA               | Sadighi et al. [92]                        |
|                       | Decision tree, KNN | Gong et al. [10]                           |

We highlight an additional significant domain where ML methods are applied within the framework of reactor physics: the prediction of state parameters. The methodologies for parameter prediction are more varied than those employed to solve the governing equations of nuclear reactions. This diversity underscores the ongoing potential for research innovation in the field. It is noteworthy that this area often intersects with the preceding section, given that the equations in question encapsulate the microscopic dynamics of neutron transport—a fundamental and substantial foundation for the accurate prediction of state parameters

terms of accuracy improvement in recent studies. Berry et al. [30] trained an ANN and random forest (RF) classifier to determine whether a given 20-group energy structure enabled a multi-group collision probability model to compute an accurate neutron multiplication factor in LWR lattice simulations, and the trained model achieved classification with 95.3% and 95.5% accuracy, respectively. Ren et al. [81] explored the potential of utilizing Long Short-Term Memory (LSTM) neural networks to predict the multiplication factor in nuclear reactor physics, modeled the multiplication factor with the first cycle of loading the BEAVRS core for 0–300 days of full-power operation, and adjusted the appropriate parameters to make the predicted  $k_{\text{eff}}$  within 2 pcm absolute error.

Oktavian et al. [72] first developed a DNN-based error correction model with high-fidelity data for a 2×2 BWR core set, generated by the Monte Carlo method. They utilized multiple ML methods to generate high-fidelity data from the error correction of low-fidelity data. Compared with traditional numerical methods, such as Monte Carlo simulations, the results of the DNN and XGBoost methods are better. The error of  $k_{\text{eff}}$  for PARCS assisted with DNN and XGBoost correction models can be reduced from 200–300 pcm to approximately 50 pcm or lower on average. Bei et al. [82] developed a BP neural network-based surrogate model for the fast prediction of the multiplication factor in the core, based on data modeled and simulated using the Monte Carlo method for the different operating states of the MSR experiment. The maximum absolute error (MAE) of the  $k_{\text{eff}}$  prediction surrogate model was reduced

to approximately 70 pcm, significantly improving the accuracy of the core calculations compared to traditional physics-based models, where most errors were within  $\pm 50$  pcm, with a maximum absolute error of 70 pcm, demonstrating the reliability of the  $k_{\text{eff}}$  surrogate model.

## 2.2.2 Neutron cross section

In the two-step approach, which is currently the most commonly used in nuclear reactor simulations, the first step is the generation of uniform few-group cross sections [83]. Taking high-temperature gas-cooled reactors (HTGR) as an example, to improve the accuracy of the reactor physics module of the HTGR Engineering Simulation System (HTR-ESS), more accurate computational models of the cross section are generally built in real-time simulations. However, owing to the complex nonlinear relationship between the cross section parameters and other state parameters, there is no generalized model [84, 85].

Ravichandran et al. [86] trained DNN to predict the value of the cross section of 2D pin cell model and 2D lattice model nodes of a PWR and confirmed the feasibility of this method in PWR. They also mentioned the optimization of the algorithm with the help of transfer learning (TL) to reduce the dependence on a large dataset.

Vicente-Valdez et al. [84] proposed to support complex tasks of nuclear reactor evaluators with the help of ML technology. They developed decision tree and KNN methods to fit nuclear data and infer the induced reaction cross sections for neutrons. The predicted values based on the ML methods

matched the new measurements accurately. In their work, they explored proof-of-concept models that rely on learning the underlying patterns of cross sectional data from other radionuclides, demonstrating that ML models can assist traditional physics-guided models and play a role in nuclear data evaluation. They [84] also pointed out that incorporating the ML model into the nuclear data module can enable evaluators to make faster, unbiased decisions in areas of uncertainty and better inform data measurement activities in the most sensitive areas of future Experimental Nuclear Reaction Data (EXFOR). Finally, Ivanov [87] explored the use of ML methods to address the problems faced when approximating neutron cross sections using NNs.

For industrial applications, especially in the absence of data, Sun et al. [88] investigated the ( $n$ ,  $2n$ ) reaction cross section of fission products using ANN and XGBoost models to predict these reaction cross sections. ANN predictions with mean absolute percentage error (MAPE) deviations of less than 10% accounted for more than 85% of the test set. To meet the real-time requirements in ESS, Li et al. [89] proposed the use of a DNN to consider the complex nonlinear relationships among the reactor variables and used tree regression (TR) to obtain an accurate cross section and optimize the cross section calculation among them.

ML methods must be used with caution for different problems. Martin et al. [83] investigated a DL framework for the mathematical representation of multi-group cross sections in the Griffin reactor multi-physics code for two-step deterministic neutronic calculations. They provided a technique for propagating cross sectional model errors to  $k_{\text{eff}}$  using sensitivity coefficients with first-order uncertainty propagation rules. They also showed that the MLP achieves an accuracy from 1765 to 800 pcm in cross sections with nonlinear dependence, particularly in the case of rough networks. For linearly dependent multi-group cross sections in sodium-cooled fast reactors (SFR), simple linear regression is more suitable.

Cross section prediction is beneficial for high-precision fuel depletion calculations. Leniau et al. [90] discussed the characterization of the spatial distribution of Pu in nuclear fuel as well as the establishment and validation of burnup models. They obtained the spatial distribution of Pu using the Latin Hypercube Sampling (LHS) method and proposed a method based on NNs, which can be used to build a fuel loading model for PWR loaded with MOX fuel and a cross section predictor. The average cross section predictor can complete the fuel consumption calculations with high accuracy in a short time.

Related studies have also explored the internal structure of the cross section in terms of its internal structure. To determine the resonant structure of the cross sections, Nobre et al. [91] applied ML methods to automatically assign the angular momentum quantum numbers of the resonances.

### 2.2.3 Neutron flux

ML techniques have been used in neutron flux flattening problems since 2002, when Sadighi et al. [92] proposed combining a continuous Hopfield NN with a simulated annealing algorithm (SA) to guarantee an optimal solution with reduced computational effort. A good result was obtained in solving the neutron flux flattening problem at the Bushehr nuclear power plant.

To address the problem of calculating the continuous neutron flux distribution, Xie et al. [34] proposed two boundary processing methods based on ANN and compared their accuracy and efficiency by analyzing benchmark tests. The experimental results show that the latter method is more accurate. They further proposed a trial function construction method to generalize its application.

Zhang et al. [71] proposed a DL-based agent model to replace the traditional diffusion equation solver and thus predict the flux and power distributions of reactor cores. They designed a CNN inspired by a fully convolutional network (FCN) and obtained positive results.

By combining reduced-order modeling and ML methods, Gong et al. [10] proposed a data-enabled physics-informed machine learning (PIML) digital twin model to predict high-dimensional outputs, such as neutron flux distributions and power distributions in reactor cores. Using KNN and decision trees, they attempted to demonstrate the effectiveness of HPR1000 for online monitoring. This study also explores how the model can be used to quickly reconstruct the neutron field for real-time input parameters.

Furthermore, Bei et al. [82] developed a BPNN-based proxy model for the fast prediction of the channel-by-channel neutron flux distribution in the 3D channel of an MSR core. They generated dataset samples by simulating different operating states of the MSR using Monte Carlo methods and trained and optimized a proxy model. In addition, Chen et al. [35] analyzed the neutron flux in the help of multiple regression methods. As mentioned previously, Elhareef et al. [43] applied the PINN method to a neutron diffusion model to solve a loosely coupled reactor model and used it to optimize the NN hyperparameters, which resulted in a significant reduction in the predicted neutron flux error.

ML techniques have also been used for data enhancement, with Berry et al. [93] exploring the use of CNN to improve the resolution of neutron flux statistics in Monte Carlo simulations.

## 3 Problems in reactor physics dealt with ML methods

ML methods have significantly enhanced the foundational framework of reactor physics. Theoretical advancements have also addressed the various challenges inherent in

traditional nuclear reactor domains. Progress in steady-state problem resolution is expected to accelerate the application of ML in complex scenarios, including reactor operation simulations and safety designs. Similarly, advancements in transient problem solving will significantly improve the monitoring and maintenance of nuclear power plants.

The burnup issue, which is intricately linked to both steady-state and transient phenomena, represents a critical area of study. Conventional analyses often prioritize the prediction of specific phenomena or the management of isolated variables, frequently overlooking interpretability. However, an accurate prediction of burnup can substantially improve the interpretability of these analyses. Research in this area has the potential to optimize fuel management, support dynamic decision-making, and advance the study of nuclear fuel cycles.

Additionally, this study elucidates several ML-driven solutions to broader challenges in the field, such as issues of interpretability and advancements in radiation transport equations. These innovations are poised to significantly influence the future development of reactor physics.

### 3.1 Steady-state problems

The steady-state problem is significant in nuclear reactor physics, focusing on the parameters or distributions of key variables as the system approaches its final reaction state. ML technologies play a crucial role in solving the governing equations in reactor physics. In steady-state problems, neutron diffusion often involves multiple energy levels and heterogeneous media, leading to heterogeneous neutron diffusion issues. Additionally, within the governing equations of reactor physics, the  $k$ -eigenvalue of the reactor can be predicted without explicit solving, known as the  $k$ -eigenvalue problem.

Reactor performance refers to various factors, such as neutron flux distribution, fuel utilization efficiency, and thermal-hydraulic behavior. The key parameters influencing reactor performance include temperature distribution, flow rates, and pressure conditions within the reactor core. The reactor performance prediction model integrates a reactor physics model and a thermo-hydraulic model, which allows for the prediction of thermal-hydraulic parameters, such as temperature distributions in the core.

#### 3.1.1 $k$ -eigenvalue problems

The  $k$ -eigenvalue problems based on diffusion theory have several applications in ML techniques. One of the earliest applications of ML in the prediction of the neutron diffusion equation dates back to 1999. In this study, a query-based adaptive retraining approach was developed, which involved reconstructing a two hidden-layer neural network

for the rapid prediction of the eigenvalues of the fundamental mode of the neutron diffusion equation, specifically the effective multiplication factor ( $k_{\text{eff}}$ ) [94].

Based on their earlier work [77], Elhareef et al. [78] investigated solving the  $k$ -eigenvalue diffusion equations in a multiregional configuration subject to a set of Robin boundary conditions, and the relative percentage errors of the two example  $k$ -eigenvalues were approximately 0.77% and 1.2%, respectively. They further investigated the forward PINN method, which was applied to the solution of the neutron diffusion equation for single and multi-energy groups, by using a freely learnable parameter to approximate the eigenvalues and a new regularization technique to exclude zero solutions from the PINN frameworks [43]. The computed results are compared with the FEM solutions of the neutron fluxes and power iteration solutions of  $k_{\text{eff}}$ . The errors in the fluxes ranged from 0.63% for a simple fixed-source problem to 15% for a two-set  $k$ -eigenvalue problem. The predicted  $k$ -eigenvalue deviations from the power iteration solver ranged from 0.13% to 0.92%. To solve the problem of solution infinity when calculating the neutron diffusion equation using deterministic methods, Li et al. [95] used the power calculation equation as a supplementary equation to form a system of differential-integral equations with the neutron diffusion equation and designed a coupled numerical and machine learning (ML) algorithm based on the finite volume method of gradient updating for the system of equations, which was applied to calculate the neutron flux densities and volumetric heat rates of the energy groups at specified powers.

In a recent study, Yang et al. [7] proposed a data-enabled PINN (DEPINN) for solving the neutron diffusion eigenvalue problem. They [96] also performed uncertainty analysis and further numerical studies, and the proposed interval loss function to deal with noisy a priori data items significantly improved the robustness of DEPINN to noise. The proposed method is expected to solve practical nuclear engineering problems in the field of nuclear reactor physics in the presence of observed data (with noise). Furthermore, they also studied the Generalized Inverse Power Method Neural Network (GIPMNN), Physics-Constrained GIPMNN (PC-GIPMNN), and Deep Ritz Method (DRM) to solve the  $k$ -eigenvalue problem in neutron diffusion theory, among which the PC-GIPMNN method performed the best, and the accuracy of the ML method was very good in all the cases, the ML method accuracy outperformed FEM and was not affected by meshing [48].

#### 3.1.2 Reactor performance prediction

As described in the introduction, small reactors are currently being developed as the fourth generation of advanced reactors [4] focusing on reactors such as TFHR. These small

reactors are usually located in remote areas for energy supply [27]. To achieve autonomous control of reactor systems with minimal intervention, thereby enabling long-term, stable, and efficient operation of nuclear reactors while reducing costs, Zeng et al. [27] investigated the autonomous control of small reactors. Their study focused on predicting the performance of the system in a steady state. They developed an ML-based performance prediction model that integrates a reactor physics model and a thermo-hydraulic model trained using the SVR method. This model was designed to predict the reactor core behavior and its future evolution. The system comprised two main components: a prediction module and a decision-making module, which worked together to accurately and efficiently assess the future operational conditions of the reactor.

### 3.1.3 Temperature field prediction

Temperature prediction also serves as a key to the optimization of nuclear reactors, and with the help of accurate prediction, we can achieve temperature regulation. In the field of nuclear power generation, reactors with heavy water coolants and moderators are widely used, and monitoring the moderator state is crucial to ensure the proper operation of the plant [26]. Starkov et al. [26] focused on the prediction of the temperature field of the nuclear reactor moderator under steady-state conditions and established a prediction system for the temperature of the heavy water moderator. They predicted the temperature distribution in the core cross section based on the cellular neural network architecture. Based on this, continuous optimization of the moderator can be achieved in the future.

Additionally, related studies have focused on predicting critical conditions, particularly the temperature. Park et al. [54] employed a ML model to predict wall temperature at critical heat flux (CHF), a crucial parameter in nuclear reactor heat transport. The CHF marks the transition from nucleate boiling to transition boiling and serves as a key indicator of the reactor performance under steady-state operating conditions in terms of heat transport efficiency.

### 3.1.4 Power prediction

In the operation of a nuclear power plant, ensuring a homogeneous radial power distribution in the reactor core is essential to avoid local overheating and ensure safe operation. The study [97] used the group data processing method (GMDH) to predict the axial power and axial offset of the reactor core, as well as the parameters for the fuel assembly. Using the GMDH algorithm, the researchers were able to reconstruct the axial power offset across the reactor core from the in-heap detector signals and determine the optimal

relationship between the detector signals, core axial power, and axial offset [97].

The performance of the reactor can also be effectively assessed by predicting the power distribution in the steady state. This is crucial because the power distribution directly influences the temperature distribution and the transport and migration of fission products within the reactor. In Ref. [98], lattice physics calculations were used to generate data to find analytical expressions for the radial power distribution in fuel cores, with the help of ML techniques to find representative expressions. Daniell et al. [99] designed and compared several Multi-Stage DNN (MSDNN) architectures for predicting the final steady state power of a research nuclear reactor after power variations. The results show that MSDNN models tend to perform better than standard feed-forward neural networks in terms of accuracy and generalization.

The use of DNN continues to be a viable alternative to standard physics modeling in nuclear systems and engineering. Alam et al. [32] attempted to develop a multi-stage prediction model consisting of 2 feed-forward DNNs to determine the final steady-state power at each transient in a real reactor facility. They separately output a resolution representing the large frequency band power output, which is used as an input to realize the prediction. Physical information is collected from the initial conditions of the transient and the final steady state [32]. The final combined model achieved a classification accuracy of 96% and an absolute prediction accuracy of 92%.

Furthermore, Wan et al. [100] proposed a neural network-based variable universe fuzzy control method for regulating power and axial power distribution in large PWRs. By establishing fuzzy inference rules based on a two-node reactor dynamics model and adopting a variable universe approach to design the input scaling factor, optimized online via a neural network, the method achieves precise control of reactor power and spatial distribution. The simulation results indicate that, under transient conditions, the control performance of this method is significantly superior to that of conventional fuzzy controllers.

### 3.1.5 Power peak factor estimation

The problem of computing the PPF is directly related to the thermal stress and potential local risks of nuclear fuel rods. Under steady-state conditions, it reflects the ratio of the maximum local power density to the average core power density reached by the nuclear reactor after a long period of operation. To address the problem of accurate estimation of the PPF, Bae et al. [21] developed a model to process the signal and predict it accurately using the measured signals from the reactor cooling system. The model is based on the

SVR method and determines the NN weights by solving quadratic programming problems.

In practice, this approach demonstrates superior generalization ability compared to traditional ANN when addressing nonlinear problems, resulting in lower prediction error. In the context of solving the fuel loading problem, Trontl et al. [22] and Hedayat et al. [101] focused on optimizing the PPF, which facilitated precise regulation of core fuel loading. Tayefi et al. [23] further optimized fuel management strategies to enhance operational efficiency and safety, ensuring that the nuclear reactor operates under optimal conditions over long-term use. Additionally, they utilized the Hopfield neural network (HNNA) to identify the optimal distribution of axial enrichment variations, which effectively reduced the peak neutron flux and power peaking factors [102].

### 3.1.6 Core loading pattern optimization

The prediction of a core loading pattern or reload strategy is a typical reactor core design task that involves optimizing the material composition, geometrical arrangement, and thermal-hydraulic parameters of the core. This optimization process must also account for constraints related to economic considerations, safety standards, and nuclear safeguards. These strategies aim to reduce fuel cycle costs while ensuring safe and efficient reactor operation. Conventional optimization usually consists of nuclear physics computational codes that rely on engineering judgments, heuristic rules, optimization algorithms, and evaluations, which are typically computationally intensive processes. To ameliorate this problem, Trontl et al. [22] quickly evaluated the core loading pattern using SVR methods, thus significantly reducing the computational time.

Hedayat et al. [101] explored the idea of using ANN to develop a rapid evaluation system for assessing and optimizing core parameters during reactor fuel reloading, which are essential to ensure optimal performance and compliance with safety standards during long-term operation.

## 3.2 Transient state problems

Transient simulations, particularly those involving reactor core dynamics during operational changes or disturbances, require a detailed understanding of reactor kinetics, thermodynamics, and control mechanisms. Advanced models are crucial for predicting and mitigating the effects of transient events that can impact the stability and safety of reactors.

Precise prediction of reactor neutron dynamics not only offers a more reliable theoretical foundation for core nuclear design but also serves as a critical reference for guiding the safe operation of actual reactors, thereby helping to prevent core transient accidents.

A transient is defined as an event during which a nuclear plant transitions from one state to another, the latter of which may be abnormal. Based on diffusion theory, Fick's law serves as a  $P_1$  approximation of the neutron transport equation, commonly referred to as the telegraph equation [103]. However, this formulation neglects the time derivative term of neutron flow density, limiting its ability to accurately depict the actual neutron transport process during transient events [64]. Theoretical models for transient calculations primarily include point reactor kinetic (PRK) models based on diffusion equations and nodal block diffusion neutron kinetic calculation methods that incorporate component homogenization [104].

The key factors influencing transient behavior include Doppler reactivity, which responds to changes in the fuel and coolant temperature. Traditional models, such as PRK models, are commonly used for transient calculations; however, they often have limitations in representing the full dynamics of the reactor during transient events. To address these issues, more advanced models, including those based on nodal block diffusion neutron kinetics, have been employed for more accurate predictions. Furthermore, the integration of machine learning (ML) models has shown promise in enhancing the accuracy of transient predictions and reactor control, allowing for better decision-making during these critical periods. These advanced methods can provide more reliable simulations of transient reactor behavior, which ultimately supports safe reactor operation and management.

### 3.2.1 Doppler reactivity

The Doppler reactivity coefficient is a key safety parameter of the core, which is determined during the design phase alongside the moderator reactivity coefficients. In 3D reactor core behavior analysis, these reactivity coefficients are predicted but are not required by solvers. The solvers consider local neutronic and thermal-hydraulic feedback through nodal or homogenized cross sections provided to them. Only point kinetics models (PKM) require an explicit input of reactivity coefficients. However, PKM is inherently fast; and therefore, there appears to be no need to replace it with an AI-based model to enhance its speed. Choi et al. [105] developed a comprehensive reactor dynamics model incorporating point kinetics equations (PKE), a thermodynamics model for hot water (TH), and a xenon (Xe) dynamics model to facilitate the automatic control of small modular reactors (SMRs). In a related study, Dorde et al. [33] proposed a method for calculating the Doppler reactivity in conjunction with the PRK model for Sodium Fast Reactors (SFRs), which was based on an ANN and yielded similar or even better performance.

Furthermore, the startup transients of the Purdue University Reactor-1 (PUR-1) were monitored using a reactivity



feedback scheme. This involved the use of experimental parameters derived from a neutron source, providing valuable insights into the behavior of the reactor during the initial startup conditions. The integration of advanced modeling techniques and real-time monitoring is essential for enhancing the safety and operational efficiency of modern nuclear reactors. These studies underscore the importance of accurately calculating the Doppler reactivity and the potential benefits of incorporating machine learning methodologies in reactor dynamics.

### 3.2.2 Behavior prediction

The behavior of reactors undergoing rapid changes or transient events must be predicted. Traditional numerical methods are time-consuming and susceptible to accumulated rounding errors or floating-point overflow in the transient state. Therefore, Pirouzman et al. [73] proposed a cellular neural network-based simulation of complex nuclear reactor behaviors. Specifically, the method simulates the time-space response of the flux distribution in a two-dimensional Cartesian geometry, which solves the problem of behavior prediction. The model is well stabilized and can be accurately analyzed to provide fast and accurate solutions for complex and rigid models.

Park et al. [106] proposed an evolutionary algorithm, the GMDH algorithm, to process and analyze real-time data obtained from detectors inside the reactor to reconstruct and monitor the axial power distribution of a nuclear reactor. The algorithm is robust to different power distributions and can cover the entire reaction cycle, thus monitoring and evaluating the behavior of nuclear reactors in real time.

Utilizing extensive data from the Multi-Application Small LWR (MASLWR) integrated test facility at Oregon State University, Gomez Fernandez et al. [25] developed an NN topology designed to simulate and predict the behavior of a nuclear reactor during a loss-of-feedwater transient (LOFW). This NN model effectively captures the dynamic changes in various physical parameters within the reactor during the LOFW event, providing a robust tool for analyzing the reactor response under such critical conditions.

In the previous subsection on the application of ML methods in the steady state, Zeng et al. [27] investigated the prediction of steady-state properties for small reactors. Similarly, for the transient problem of microreactors, Mendoza et al. [107] proposed a power transient module that reliably identifies reactor operation as steady state, power rise, or power fall, using data from a large-scale simulator. They also explored various data-driven methods to accurately assess power transients, namely, principal component analysis, SVM, DNN, and CNN [107].

To identify the state of a nuclear reactor, Zubair et al. [108] developed a model that includes the primary and

auxiliary systems of a nuclear power plant. In addition, it includes models of the control system and instrumentation used to monitor and regulate the reactor as an important component of data extraction and transient modeling as an integral component of data extraction and transient modeling. Based on the data generated by the Western Services Cooperation's General purpose PWR (GPWR) simulator as well as MATLAB tools, they [108] simulated nine different transient events under twelve different initial conditions to create a dataset with 72,000 observations. Nine types of classification models (a total of 33 predefined models) were trained and validated using a classification learner application. The Neural Network Classifier had the highest average accuracy of 90% in the validation of the ML-based approach. The study maintained a low execution and computation time while achieving high accuracy.

In a further study, to optimize the model, the study [109] integrated feature selection using the minimum redundancy maximum relevance (mRMR) algorithm. As a result, the KNN model achieved 97% of the highest accuracy in the primary system, while the effective linear discriminant and logistic regression models obtained 99% of the highest average accuracy in the secondary system [109].

### 3.2.3 Forward and inverse problems

The real-time estimation of PPF is also important under transient conditions. This is needed to capture the rapid changes in PPF due to changes in operational variables, including control rod movement, to accurately detect and respond to special safety issues. Bae et al. [21] investigated the capture of transient PPF changes based on the SVR method. Focusing on the VVER-1000 reactor core power distribution problem, Pirouzman et al. [24] estimated the relative power distribution and PPF of the reactor core using ANN. They first monitored the radial RPD of the core and screened the axial relative power of the fuel assembly to detect the PPF of the core.

To achieve real-time power prediction, Gong et al. [38] proposed a reactor physics digital twin model that simultaneously solves the positive and negative problems of predicting power-given parameters and additional power field measurements to solve the input parameters of operation. They [38] developed a non-intrusive forward model utilizing a Singular Value Decomposition (SVD) Autoencoder (AE) downscaling model, in conjunction with machine learning methods such as KNN and decision tree. The test results demonstrated that this approach outperforms traditional reduced-order methods, such as the Proper Orthogonal Decomposition (POD). Regarding the inverse problem, they investigated a generalized latent data assimilation method to achieve real-time construction of the inverse model characteristics by evaluating the forward model

multiple times [38]. Furthermore, Gong et al. [10] rapidly reconstructed the reactor's high-fidelity neutron field with real-time input parameters based on the online situation. They simulated different scenarios, such as burnup, control rod insertion step, power level, and coolant temperature, over the life cycle of the HPR1000, demonstrating the role of transient problem solving in online monitoring.

### 3.2.4 Response decision

Anil et al. [110] predicted future reactor states under possible control strategies, particularly for reactor systems under transient conditions, to evaluate and determine the optimal control strategy for the autonomous control of nuclear reactors. The prediction model, based on the initial and boundary conditions, can predict the fuel centerline temperature with predictive uncertainty and predict the future reactor state for all possible control strategies to select the optimal control strategy in the face of contingencies.

Konstantinos et al. [47] used a point kinetic model as a basis for predicting the neutron density in transients with the help of transfer learning PINN (TL-PINN). This is an alternative to the traditional reactor transient modeling. Transfer learning achieves a significant performance improvement compared to PINN, greatly reducing the number of iterations required for model training. They generated transients with different ranges of experimentally relevant variables using the PUR-1 experimental data.

Because the extreme stress of operators in most nuclear accident scenarios is prone to operational errors, ML models can provide real-time support and advice and act as expert systems to assist in accident handling and decision-making. Based on this idea, Nguyen et al. [111] developed a multivariate time-series ML meta-model to predict the transient response of a nuclear power plant experiencing steam generator tube rupture (SGTR). The model employs a hybrid CNN-LSTM model of recurrent neural networks (RNNs). They also implemented Bayesian Neural Networks (BNNs) to address the uncertainty in the prediction. The final model successfully captured the latent features of the data, and the BNN-LSTM approach provided additional monitoring of the level of uncertainty associated with heap prediction [111].

The successful application of LSTM extends beyond this point. Bae et al. [112] proposed a data-driven prediction model based on a multi-step prediction strategy and ANN. By testing MLP, RNN, and LSTM, they finalized a multi-input multiple-output strategy and LSTM, which successfully addressed multivariate problems under multiple emergencies of incident handling. The model not only achieves prediction accuracy but also guarantees accident transient prediction capability, with a prediction time of only 0.06 s.

### 3.2.5 Thermo-hydraulic coupling

The nuclear reactor is a complex system with a wide range of physical fields such as neutron density field, flow field, temperature field, etc., widely present in the reactor system [113]. These physical fields interact with each other; therefore, there is a strong coupling relationship between them. These coupling relations are not negligible during reactor operation, particularly during transient processes. Additionally, for neutronics, the neutron fluence rate determines the distribution of fission power inside the core, which affects the temperature field of the fuel rods in addition to that of water, and ultimately changes the entire temperature field. In thermal hydraulics, the thermodynamic parameters strongly affect the macroscopic cross section. The interaction of these physical fields forms the basis for the coupling of neutronics and thermo-hydraulics [114]. Therefore, we will broadly introduce machine learning applications in the scenario of reactor thermal hydrodynamics coupled with reactor physics.

In recent years, the application of ML techniques in nuclear reactor thermo-hydrodynamic coupling and related areas has achieved remarkable progress, offering innovative solutions for the real-time prediction, optimization, and control of complex systems. For instance, Zhang et al. [115] proposed a neural network-based rapid prediction method for multi-physics field coupling in heat pipe reactors. By replacing traditional numerical modules with neural networks, this method achieves high-precision coupling predictions for multiple physical domains (e.g., neutronics, thermal, and mechanical) while reducing computation time from several hours to less than four minutes—without compromising key parameter accuracy (e.g., maximal stress difference <2 MPa, average fuel temperature difference <3 K). Moreover, the approach requires relatively modest training data and permits dynamic model correction and optimization based on prediction performance, thereby offering significant support for early accident warning and on-site deployment.

Traditional approaches often decouple these phenomena, for instance, by using one-way coupling, where neutronics and thermal hydraulics provide boundary conditions for fuel performance analysis. However, this simplification may overlook essential core-wide interactions. To address this, Che et al. [116] developed a machine learning-assisted surrogate model that fully integrates coupled neutronics, thermal hydraulics, and fuel thermo-mechanics. By combining look-up tables with advanced ML algorithms, including rule-based techniques for effective feature extraction, the surrogate model accelerates the simulation time by up to four orders of magnitude relative to conventional codes (e.g., FRAPCON) while preserving key accuracy metrics. This approach enables more realistic full-core predictions

and facilitates the tighter integration of fuel performance into core design optimization.

In addition, Aghili Nasr et al. [117] tackled a core challenge in coupled simulations: dynamically updating neutron cross sections as a function of the evolving state variables. Their method employs Gaussian Process Regression (GPR) to substitute traditional logarithmic correlations for temperature-dependent cross section updates. Implemented within a multi-physics framework based on OpenFOAM, the GPR approach was validated for benchmark problems and a 2D axisymmetric Molten Salt Reactor configuration. The results demonstrate that, particularly for isotopes with prominent absorption resonances (e.g.,  $^{232}\text{Th}$  and  $^{238}\text{U}$ ), the method significantly influences the effective multiplication factor ( $k_{\text{eff}}$ ) and transient peak power predictions, highlighting the importance of robust coupling for reactor safety analysis.

Overall, these studies underscore the transformative potential of advanced surrogate modeling and ML techniques in capturing the nuanced interplay between reactor physics and thermal hydraulics. These approaches not only substantially reduce computational burdens and enhance predictive fidelity, but also offer flexible and efficient strategies for regulating reactor operations. The vast application potential of ML in improving multi-physics field coupling and thermo-hydrodynamic integration is pivotal for achieving the safe, economical, and intelligent operation of nuclear power plants. For a comprehensive review of ML applications in thermal hydraulics, readers are encouraged to consult [118].

### 3.3 Fuel burnup problems

Traditional methods based on the burnup equation include higher-order Chebyshev rational approximation [119] and Krylov subspace methods [120]. The direct use of ML technology in burnup calculation, burnup distribution prediction, nuclide density prediction, etc., has already achieved a significant breakthrough.

Burnup calculations are critical for understanding and predicting changes in nuclei inventories and mass flow evolution in an entire fuel cycle, from the mine to the final disposal [90]. Burnup modeling allows the simulation of the operating conditions of reactor units and the dynamics of fuel cycle facilities to optimize fuel management and improve the efficiency of nuclear energy. Accurate burnup predictions are also important for ensuring the safe operation of nuclear reactors and supporting fuel cycle decision-making. In dynamic fuel cycle simulation tools, these isotopic compositions are unknown until the code is executed. Therefore, models are required to calculate the fuel burnup [90]. Burnup prediction includes the burnup distribution [121] and nuclide density distribution [122]. In addition, ML techniques have some applications in other problems [35].

#### 3.3.1 Optimization of burnup calculation

To simplify and accelerate the process of pressurized water reactor burnup calculations, Leniau et al. [90] proposed a method to generate a precalculated set of fuel burnup calculations. They developed an NN-based approach. Their method [90] was applied to the dynamic fuel cycle simulation tool CLASS to predict the Pu content and average cross section in the fuel using a neural network, which significantly improved the computational efficiency and accuracy. The method was able to complete burnup calculations in less than a minute and had an average error of only 0.37% in predicting Pu content, demonstrating its potential for nuclear fuel cycle management and burnup prediction.

On this basis, Courtin et al. [123] investigated the MOX extended fuel nuclide prediction. Their proposed fuel loading model, based on infinite multiplication factor ( $k_{\text{inf}}$ ) calculations, predicts the amount of Pu in the fuel required to reach the target burnup, as well as the enrichment of U in specific cases, with an accuracy of 270 pcm and a deviation of less than 4% for the primary nucleus at the end of the cycle (EOC).

To perform safeguards, the spent nuclear fuel needs to be checked for the correctness of the fuel assembly declarations and the completeness of the relevant declarations for each fuel assembly, i.e., it is determined that the spent fuel assembly does contain nuclear material and that no diversion of a part of the assembly has taken place [124]. Based on simulated pressurized water reactor fuel data, Grape et al. [124] used random forest regression to explore the predictive power of fuel parameters for the initial enrichment, burnup, and cooling time.

#### 3.3.2 Burnup distribution prediction

Accurate prediction of the burnup distribution is also crucial for fuel reloading design and optimization, which is essential for the safety and economy of the reactor. However, owing to the heterogeneous flow distribution in the reactor core and the manufacturing deviation of each component, there is a deviation between the actual and the simulation results, leading to an error in the power distribution that is subsequently transferred to the burnup distribution [121]. Guo et al. [121] proposed a data assimilation method. They first combined the measured values of the power distribution with the results of the numerical simulation, established the relationship between the burnup distribution and power distribution using ANN, and finally calibrated the burnup distribution using the 3D variational (3DVAR) method. The method was validated on the CNP1000 PWR, and the error in the burnup distribution was significantly reduced.

### 3.3.3 Nuclide density prediction

A related study developed and validated a DL-based model for predicting the burnup nuclide densities. To predict the nuclide densities of  $^{235}\text{U}$ ,  $^{239}\text{Pu}$ ,  $^{241}\text{Pu}$ ,  $^{137}\text{Cs}$ , and  $^{154}\text{Nd}$ , Lei et al. [122] used the mean square error (MSE) of the DNN as a loss function by comparing it with the relative error of a multilayer perceptron model. They found that DNN overcame the problem of excessive prediction errors of traditional ML algorithms in the low-burnup region and performed better in the middle and high-burnup regions, proving the feasibility of ML techniques for nuclide density prediction.

### 3.3.4 Other fields in burnup

To analyze the equilibrium burnup state of molten salt reactors (MSRs), Chen et al. [35] generated equilibrium and non-equilibrium state neutron information of fuel assemblies with different geometrical parameters as a dataset, and quickly filtered the models for the equilibrium burnup state and predicted the neutron fluxes and multiplication ratios using 15 different ML regression algorithms. The LGBM model performed the best.

Soto et al. [125] found that with the help of ML methods, it is possible to achieve a significant improvement in accuracy over a short fuel cooling time, increased robustness to spectral compression, and competitive burnup prediction even when only background signals are used, which is difficult to achieve with conventional methods.

The burnup of nuclear reactors is also affected by the interaction between the fuel and cladding, which is currently the subject of more frontier studies [126]. The literature indicates that the ML method is expected to be used in conjunction with energy dispersive X-ray spectroscopy (EDS) analysis of scanning electron microscopy collected in this study for the analysis of high-magnification back-scattered electron (BSE) datasets to facilitate the rapid and consistent extraction of statistical information on fuel-cladding chemical interaction (FCCI).

## 3.4 Other problems

### 3.4.1 Observable measurement descriptions

Accurate definitions of nuclear physics observables become difficult since the information from differential nuclear physics experiments and theories is usually subject to large uncertainties, thus making the precise definition of nuclear physics observables challenging. However, the overall experimental data representing the applications of these

observables are usually more precise. Simultaneously, there is too much experimental data to identify problems in the observables through human expert analysis alone [55].

To describe these quantities, Neudecker et al. [55] proposed an analytical approach to identify groups of observable measurements in nuclear physics that may lead to biases in integral experimental simulations using the Random Forest algorithm and SHAP metric.

In a practical application, the study characterizes the fission observable measurements of  $^{241}\text{Pu}$ . They [55] combined differential experimental data and theoretical modeling to determine that the  $^{241}\text{Pu}$  fission cross section may be the main cause of the simulation bias. The high-energy interval data for  $^{239}\text{Pu}$ , which could not be accurately described, were still able to narrow down the range of nuclear data that could be problematic. This demonstrates the successful application of ML technology in the description of observed quantities and its wide range of prospects.

### 3.4.2 Radiation transport problems

The radiation transport problem encompasses various types of radiation, including neutron transport in reactor physics. This describes the radiation flux through a heterogeneous medium. For radiative transport problem, traditional ML methods are difficult to apply because of the large computational cost of creating data through simulations. Huhn et al. [53] investigated the PINN method to solve the radiative transport problem in the absence of data. They also proposed the application of Fourier features in the algorithm, which yielded good performance for heterogeneous problems. For sampling, they investigated heuristic-based methods. In a practical set of one-dimensional radiative transport problems, PINN produces consistent results with traditional method solutions under fine grids [53].

## 4 Reactor physics: data and applications

The previous sections offered a thorough exploration of how ML technology can enhance various facets of reactor physics, encompassing the architecture of governing equations, state parameters, and their application in both steady-state and transient problems. This section will shift the focuses on the impact of ML methods on performance improvements in real-world applications. Specifically, it examines advancements in data processing and identification, referred to as “data in modeling” and their roles in simulation, online monitoring, and design within industrial contexts.

ML models learn patterns from large datasets. In reactor physics, these models are trained using historical data from reactor simulations and real reactor data. After training, the models can predict reactor behavior, optimize operational



parameters, and detect anomalies in real time. These models typically rely on supervised learning techniques, wherein the model learns from labeled data (e.g., reactor states and corresponding outcomes) and generalizes to make predictions for unseen scenarios.

Despite the potential of AI in reactor physics, several challenges remain. First, the complexity of reactor dynamics, which involves numerous interacting physical phenomena, makes it difficult for models to generalize across different reactor types or operational conditions. Additionally, training ML models requires high-quality, well-labeled data, which can be scarce or difficult to obtain in real time. Moreover, many ML models function as black boxes, making it difficult to interpret how they arrive at specific decisions, which can be a significant concern in safety-critical applications such as nuclear reactors.

Although ML models have shown promise in operational simulations and reactor monitoring, their accuracy is often limited by the fidelity of the data on which they are trained. In many cases, ML models are used in conjunction with traditional physics-based simulations to ensure the safety and robustness of the predictions. For example, hybrid models combine machine learning with high-fidelity reactor physics simulations to reduce the errors associated with low-fidelity models. Moreover, real-time retraining of ML models is sometimes necessary to account for changes in reactor conditions or to update the models with new data, which further complicates their deployment.

## 4.1 Data in modeling

ML methods also offer significant benefits for data processing and enhancement tasks such as model data correction, data generation, data validation analysis, and noise diagnosis. These aspects are not directly related to steady-state or transient problems but involve optimization during model preparation. As such, they are discussed in the section addressing the additional challenges.

### 4.1.1 Model correction problem

Although high-fidelity transport calculations are certainly accurate, their large number of calculations makes them difficult to apply, especially in the implementation of forecasting, where it is almost impossible to obtain direct access to high-fidelity model/data in real time. Therefore, this study considers error correction for low-fidelity models/data.

For operational simulation and real-time prediction in boiling water reactor (BWR), Oktavian et al. [127] investigated machine learning (ML) methods. Specifically, they generated initial results using a standard two-step simulation [112] process and then used an ML model to correct the errors between the high- and low-fidelity data. To

correct the errors between the nuclear reactor mechanical model and the actual reactor, Wang et al. [128] proposed a hybrid mechanism and NN approach for nuclear reactor modeling to eliminate or minimize these deviations. Specifically, based on simulation data from RELAP5, they built a point reactor dynamics model as a model of the core and calibrated it using a genetic algorithm (GA) to optimize the BPNN reactor reactivity feedback.

### 4.1.2 Nuclear data validation analysis

Nuclear data validation analysis focuses on identifying possible problems in nuclear data using ML models. This process focuses on the overall quality and predictive power of the nuclear data. As mentioned in the literature [56], ML methods assess the reliability of a large number of nuclear data features and corresponding experimental results by analyzing them in the simulation of critical nuclear experiments. These models are based on the measurements and simulations of selected key components from the International Criticality Safety Benchmark Evaluation Project (ICSBE). The  $k_{\text{eff}}$ , along with its sensitivity to nuclear data and baseline features, was used as an input to the Random Forest (RF) regression model. The RF model is employed to encode the complex interdependencies between factors such as sensitivity profiles, descriptive measurements of the nuclear data, and both simulated and experimental  $k_{\text{eff}}$  values. This approach aims to identify the nuclear data features that are most influential in predicting deviations, thereby enhancing our understanding of the underlying relationships.

A related study [84] also focused on the potential role of ML in supporting cross section evaluation and proposed a data enhancement model for neutron-induced response cross sections. Specifically, they fitted nuclear data from the EXFOR database based on decision trees and KNN to predict data for important nuclides, and the final predictions matched the measurements very accurately.

### 4.1.3 Data synthesis problem

Before building a nuclear power plant, the proliferation potential of nuclear reactors must be understood. A digital twin is a solution for identifying the behavior of nuclear proliferation reactors. Based on the parameters of the AGN-201 reactor of Idaho State University, Palmer et al. [129] discussed data synthesis techniques to generate data for training the digital twin model. Additionally, they trained the LSTM on synthetic data to further validate the application of these methods in the implementation of digital twins. The benefit of this approach is that it effectively captures the aging and sensor drift of equipment caused by environmental factors and other influences. By monitoring the error between the actual and synthesized data, the need for reprocessing the



synthesized data at the appropriate time can be signaled, ensuring more accurate and reliable monitoring and analysis over the equipment's lifespan [129].

#### 4.1.4 Noise diagnostic problems

Nuclear power plants are large and complex systems equipped with numerous monitoring sensors. Within the reactor core, it is critical to detect anomalies as early as possible to prevent irreversible effects. Although the core can accommodate only a limited number of sensors for data acquisition, neutron detectors remain highly effective in capturing perturbations, even those occurring at significant distances from the sensors. This capability is due to the intrinsic nature of fission and scattering reactions, as well as the transport of particles within the core, which allows for the detection of changes throughout the reactor system [130].

Based on the capture of anomalous states, Kollias et al. [130] used an ML method for noise capture and anomaly localization. Specifically, they performed semantic segmentation, classification, and localization for multiple simultaneous perturbations using DL models. They further developed a domain-adaptive approach and applied it to real reactor simulations.

#### 4.1.5 Data fidelity mapping

To reduce the cumulative error of long-term prediction while minimizing computational costs, Zhou et al. [131] introduced a novel prediction model known as the multi-scale physics-constrained neural network (MSPCNN). This model utilizes a multi-fidelity convolutional autoencoder (CAE) to map data of varying fidelity into a uniformly shared potential space. This approach serves two key purposes. First, it enables low-fidelity data to complement high-fidelity data during the training phase. Second, it allows the enforcement of physical constraints within the low-fidelity domain rather than at the high-fidelity level. This strategy significantly reduces the costs associated with offline data acquisition and preprocessing while ensuring model accuracy. This advancement represents a notable improvement over the traditional PINN. Additionally, the MSPCNN model is robust to noise, providing reliable predictions even under suboptimal conditions.

## 4.2 Applications

In this section, we explore the practical applications of ML methods in reactor physics in real nuclear power plants. We focus on a series of technological innovations and methodological improvements brought to nuclear power plants by the application of ML technology, especially the advancements made in the industry by the enhancements in the field of

nuclear reactor physics. We will mainly focus on operation simulation, online supervision and maintenance, and core optimization design based on actual nuclear power plants.

### 4.2.1 Applications in operational simulation

Neutron simulations of reaction processes are essential for the design and operation of nuclear reactors, serving as both a validation of safety and operational capability. Efficient simulations not only provide operators with real-time data and critical metrics to optimize power distribution and burnup and extend equipment life, but also hold the potential to significantly accelerate the design of next-generation advanced reactors [132]. A considerable body of literature focuses on the application of ML methods in reactor simulations, which will be systematically reviewed and discussed in this section.

**4.2.1.1 Massively parallel simulation acceleration** Neutron simulations rely on physical models and numerical methods that often require large volumes of data. Current codes for neutron simulations often rely on tabulated data and simplified physical models, which reduce the runtime at the expense of accuracy. High-throughput Graphics Processing Units (GPUs) and GPU-accelerated High-Performance Computing (HPC) platforms can reduce this dependence. Optimizing neutron codes and their algorithms is key to fully utilizing advanced computational power and maximizing fidelity. Dorville et al. [132] presented three computational projects aimed at improving the performance of neutron transport codes through a modular approach. The common goal of these projects is to enable neutron codes to optimally utilize the massively parallel acceleration provided by GPUs.

**4.2.1.2 Modeling and simulation of reactor physical phenomena** Anil et al. [110] enhanced the efficiency of simulation predictions by employing machine learning (ML) techniques. These ML-driven methods integrate a physics-informed bootstrap mechanism that effectively augments the model's capacity to learn the underlying physical phenomena through data-driven approaches. This approach constitutes a framework designed to guide and improve predictive modeling in ML-based autonomous control systems.

To enable simulations, Radaideh et al. [133] developed a novel modeling framework. The framework combines multi-physics simulations and real data, validated by an uncertainty quantification task, and finally integrated using ML methods. The code can simulate different physical phenomena inside the reactor, such as neutron transport, reactor dynamics, fuel depletion, two-phase flow, and fuel performance [133].

For the efficient conduct of the simulation process, Che et al. [116] explored the application of ML methods to improve the computational efficiency of the fuel performance analysis of nuclear reactor cores. They aimed to use ML techniques to accelerate full-core simulations by constructing fast-running surrogate models.

**4.2.1.3 Fuel reload for BWR** The optimization of the fuel reloading problem for a BWR usually involves combinatorial optimization, which is an NP-complete problem. An accurate reactor simulator is required from expert systems to genetic algorithms. However, conventional simulators require a significant amount of time, making optimization challenging to perform efficiently and accurately [17].

In 2003, it was proposed to adapt, modify, or even replace the reactor simulator. Based on the emerging NN model, Ortiz et al. [17] proposed replacing the nuclear reactor simulator with this model to predict several variables in the BWR optimization of the fuel changeover process, including the  $k_{\text{eff}}$  of the reactor and safety-related thermal limits. After training, the NN can provide results in a few seconds, which is a significant improvement compared to the few minutes required for traditional simulations.

Based on previous work, Ortiz et al. [18] further investigated the optimization of the loading pattern in a BWR, which was applied to find the optimal reproduction pattern for five cycles at the Laguna Verde nuclear power plant in Mexico. Moreover, Trontl et al. [22] proposed the use of a support vector regression (SVR) model to quickly evaluate and optimize the core loading patterns in nuclear reactors. This model, as a supervised learning method, can efficiently predict and evaluate different loading patterns and significantly reduce the computational time required by traditional optimization methods to improve the efficiency of core loading pattern evaluation in nuclear reactors [22].

**4.2.1.4 Operational simulation of BWR** During the operation of a BWR, the industry requires dynamic and precise control of reactivity to maintain efficient operation. Throughout the reactor cycle, adjustments are made to the insertion of control rods and the flow rate of the core; and thus, the reactivity is maintained under control [127]. Oktavian et al. [127] introduced a new methodology to use ML methods to enhance the simulation of BWR operation. The ML technique is primarily used to identify and correct problems in low-fidelity simulation results, aiming to produce a fit to high-fidelity data after data correction. This approach focuses on enhancing the regular BWR model without increasing the speed of operation, which is critical for fuel management.

Oktavian et al. [72] further tested two different ML methods, including DNN and extreme gradient augmentation models, based on data from Monte Carlo simulations,

validated in a 2×2 simulation of a simple BWR. They [134] also generalized the model to a small BWR with 88 fuel bundles and validated it in a full-core BWR with 560 fuel bundles based on Unit 1 of the Edwin Hatch nuclear power plant. They found that the model yielded good results for a range of conventional BWR operations with a fixed core design.

**4.2.1.5 Fuel loading of PWR** The fuel can usually be modeled in a dynamic fuel cycle simulation tool [90] from mining through the entire fuel cycle until it becomes spent fuel at the end of the reaction, including the nuclear inventory present in it and the evolution of the mass flow. In this process, fuel consumption, which relies mainly on fuel loading models and average cross section predictors for processing, must be studied [90]. For the PWR-MOX case, Leniau et al. [90] investigated a neural network-based approach to build a loading model and a cross section prediction model for loading MOX fuel. The former predicted the Pu content with an average error of 0.37%, and the latter realized a high-precision fuel calculation within one minute.

In addition, there are differences between the numerical simulations and actual cores. These differences can lead to errors in the simulated power and burnup distributions. To reduce these errors, Guo et al. [121] proposed a data assimilation method for PWR burnup distributions, aiming to calibrate the burnup distributions using power distribution measurements. Specifically, they used a three-dimensional variational (3DVAR) algorithm for burnup distribution calibration and applied an ANN algorithm to establish a complex relationship between the burnup distribution and power distribution [121]. Through engineering validation, this data assimilation method was successfully applied to the CNP1000 PWR in China.

In the realm of pressurized water reactor (PWR) fuel loading optimization, Wan et al. [135] developed a rapid evaluation model using an improved convolutional neural network integrated with the Inception-ResNet architecture. This model can accurately predict core parameters in approximately 0.0005 s and, when coupled with a genetic algorithm, efficiently identifies the optimal fuel loading pattern, completing the entire optimization process in approximately 20 min. This advancement not only enhances the operational safety of nuclear power plants but also improves their economic performance.

**4.2.1.6 Optimization of HTR-ESS** Based on the diffusion module in HTR-ESS, Li et al. [89] proposed a novel method that meets the real-time requirements of an ESS. They further demonstrated through numerical experiments that their method is more accurate and efficient than existing methods.

However, owing to the limited number of samples, the cross section calculation model using the traditional model

tree is easily overfitted in the leaf nodes, which leads to incorrect cross section variations of the reactor core state parameters, which further appears to be inconsistent with the reactor physics laws. Moreover, the method fails at the subspace boundary discontinuities. To overcome these two major difficulties, Tan et al. [85] improved the model with novel methods and produced a more accurate cross section compared to existing methods and fulfilled the requirement of real-time calculation. They also validated the suitability of the method using a 10 MW high-temperature gas-cooled reactor (HTR-10) simulator.

**4.2.1.7 Digital twin in simulation** A digital twin is a virtual representation of a physical asset, such as a reactor core, implemented using data and simulators to better understand the behavior of a nuclear reactor system. This concept is valuable for real-time prediction, optimization, monitoring, control, and enhanced decision-making [136]. In an early application in reactor physics, Gong et al. [38] proposed a reactor physics operational digital twin (RPODT) prototype for predicting the neutron flux and power distribution in nuclear reactor cores for online monitoring. They demonstrated the effectiveness of this digital twin using a real-world engineering case involving the HPR1000 reactor.

In the early applications of reactors, one of the key components of RPODT was simulation modeling [38]. The most unique and important physical fields for the modeling and simulation of reactor cores are the neutron field and the associated core power distribution. Therefore, Gong et al. [38] further proposed a new digital twin model based on the ML approach, which solves both the forward and inverse problems and was well validated in the core simulation of the HPR1000 reactor. The accuracy was acceptable from an engineering viewpoint.

Furthermore, they [10] explored digital twins by proposing a reduced-order model combined with ML methods. In the simulation of the reactor core modeled by two-group neutron diffusion equations, the model parameters were influenced by the input parameters over the life cycle of the HPR1000. They tested different burnups, control rod insertion steps, power levels and coolant temperatures. The study pointed out that ML-based predictive models need to be retrained each time for new reactor conditions, in which case real-time inference by digital twins (DT) would be prohibited [137]. To ameliorate this problem, Kobayashi et al. [137] investigated the feasibility of a deep neural operator network (DeepONet) as a robust agent modeling method in the context of DT-enabling technology for nuclear energy systems. The benefit of DeepONet is that it relaxes the requirement for continuous retraining, making it suitable for both online and real-time prediction components. Through testing and evaluation, the proposed method shows an improvement over traditional methods in terms of both

accuracy and efficiency. In addition, DeepONet has demonstrated generalizability and computational efficiency as an effective surrogate tool for DT components.

## 4.2.2 Applications in online monitoring

The safe operation and effective maintenance of nuclear reactors are critical. The development of economically beneficial and safe operations requires a more accurate, comprehensive, and real-time analysis of neutron parameters [138]. A real-time monitoring system is required to confirm that the relevant safety requirements are not violated during reactor operation [139]. In the current literature related to online supervision, ML techniques have been mainly applied in real-time monitoring, autonomous control, condition detection, parameter verification, signal monitoring, and fault monitoring and diagnosis of reactors. This section focuses on the ML approaches used in these applications and the practical benefits achieved.

**4.2.2.1 Real-time monitoring of reactor parameters** The operation of nuclear reactors requires real-time monitoring and adjustment to ensure that safety limits are not exceeded under various operating conditions, which challenges the time complexity and accuracy of conventional methods. To predict the PPF of a nuclear reactor, Bae et al. [21] proposed a model that is capable of predicting the PPF in a steady state and respond quickly to transient events. This, in turn, allows for a better understanding of the behavior of the reactor under different operations, and thus more accurate decision-making during supervision by the operator. They also extended the application to the core operation limit supervisory system (COLSS) as well as the core protection calculator system (CPCS), further improving the accuracy and reliability of the system [21].

Pirouzmand et al. [24] constructed a real-time monitoring system to predict the neutron parameters of a VVER-1000 core. Specifically, the training process includes obtaining different operating states by controlling different power density distributions of the control rods and then training the MLP for each state. Based on the neural network established by the above training, the method also utilizes the signals from the out-of-core neutron detectors and core parameter information to predict the axial and radial relative power distributions and PPF.

The in-core power distribution is one of the most important safety parameters in the operation of nuclear power plants [106]. The existing methods usually utilize detectors to measure a modest amount of the signal and use a fixed basis function; thus, the accuracy of the power distribution reconstruction depends on the estimation of the fitting parameters [106]. Park et al. [106] proposed the Group Method of Data Handling (GMDH) analysis to give

the optimal form of the basis function of the nuclear power shape.

**4.2.2.2 Monitoring of moderator condition** Nuclear reactors generally have water coolants and moderators. Accurate monitoring of the moderator plays a crucial role in ensuring the proper operation of a power plant [26]. Based on the reactor model designed for the CANDU Darlington heavy water reactor as training data, Starkov et al. [26] proposed cellular NNs to consider the feasibility of real-time temperature prediction for the central section of the drain vessel. Their model can analyze events inside the drain vessel, and assess the asymmetry of the heavy water volume heating, and evaluate the motion and mixing direction of the moderator flow. Using a committee of developed cellular structures, temperature anomalies can be estimated for the entire reactor volume, which can form the basis for full-scale 3D simulations of moderator conditions in the calandria [26].

**4.2.2.3 Nuclear reactor autonomous control** The autonomous control of nuclear reactors is also a supervisory application of nuclear reactor physics. The most important aspect of autonomous control is its prediction. In nuclear engineering, prediction is the process of predicting the future condition of a system or equipment based on the current signs and symptoms of failure [110]. Accurate prediction is important for strategy selection in failure situations. Anil et al. [110] built a framework to guide the development and evaluation of ML-based prediction models for autonomous control systems.

Additionally, Zeng et al. [27] developed a core behavior prediction model based on a Thorium-Fueled High-Temperature Reactor (TFHR), which integrates a thermal-hydraulic model and a reactor physics model. They utilized RELAP5-3D simulations driven by DAKOTA to simulate various operating conditions and accident scenarios, such as different reactivity insertion rates and insertion times, to generate the dataset. The experimental results demonstrate that this methodology effectively predicts and assesses reactor states, enhancing the system response and efficiency, thereby guiding the autonomous control of the TFHR.

**4.2.2.4 Fuel parameter verification** The verification of fuel parameters, which must be verified with high precision before storing fuel in inaccessible sites, is a major core process in nuclear reactors. Verification is of the correctness of the spent nuclear fuel assembly declarations and the completeness of the declarations associated with the individual nuclear fuel assemblies, with the primary goal of verification being to determine that the spent fuel assembly does indeed contain some nuclear material and that a portion of the assembly has not been diverted [138]. This serves as a major centerpiece for ML applications in reactor physics.

Traditional verification of fuel parameters is performed using analytical instrumentation. In contrast, based on simulated data and ML methods, Grape et al. [124] systematically explored the ability to predict the initial enrichment, burnup, and cool-down times of fuel parameters, independent of operator statements.

**4.2.2.5 Signal anomaly processing** To construct an anomaly detection system, it is necessary to capture the fluctuating changes in neutron flux during the operation of the equipment, which involves the ability to identify and analyze the changes in the signal [28]. Caliva et al. [140] proposed a combination of algorithms, including Convolutional Neural Networks (CNNs), Denoising Autoencoders (DAEs), and k-mean clustering, integrated into a system used to analyze neutron flux variations in the core of nuclear reactors. The results show that despite the limited training data and the influence of occlusion or noise on the signals, the perturbation sources can be localized with high accuracy, proving the effectiveness of the method for neutron flux monitoring and anomaly detection in nuclear reactors.

Moreover, Tagaris et al. [28] proposed combining wavelet signal analysis with DL techniques. Specifically, they transformed the signal into a scalar map using wavelet transform and used it to train an NN. The results show that the trained network has high accuracy in fault detection and is robust to noise interference.

**4.2.2.6 Digital twin in monitoring** Digital twin technology, an advanced simulation and analysis tool, is increasingly being used for the monitoring and maintenance of nuclear reactors. By creating a precise virtual replica of a physical system, digital twins enable simulation experiments and detailed analyses without disrupting the actual system. This approach significantly enhances the operational efficiency and safety of nuclear reactors by enabling predictive maintenance, real-time monitoring, and optimization of system performance under various conditions.

In the literature [35], Chen et al. developed a method to quickly screen and predict the equilibrium burnup state of a nuclear reactor. This method can effectively evaluate the characteristics of the fuel cycle and make rapid predictions under different operating conditions. In contrast, Prantikos et al. [39] explored the application of PINN to nuclear reactor digital twins. This approach is not only able to handle data interpolation and extrapolation problems, but also able to make effective predictions in the presence of data scarcity.

In addition, Song et al. [141] proposed a method for online autonomous calibration of a digital twin. They calibrated the data generated by the digital twin in real time by combining ML algorithms to match the actual values. The method is implemented in two phases: offline and online phases. An error database and data-driven calibration model



are first established in the offline phase and then dynamically updated and calibrated in the online phase.

Finally, Stewart et al. [142] focused on developing a real-time extrapolation method to support digital twin solutions for nuclear energy systems. They investigated the ability of the DeepONet method to make real-time predictions of the operating conditions of nuclear reactors without continuous retraining.

**4.2.2.7 Fault monitoring and diagnostic system** By leveraging ML methodologies, researchers can monitor and analyze the operational states of nuclear reactors in real time, enabling the early detection of potential faults and anomalies. This proactive approach reduces human error and enhances the safety and efficiency of reactor operations.

Core monitoring techniques generally encompass methods for detecting core anomalies, characterizing and locating these anomalies, and ultimately classifying them based on their potential impact on the safety and availability of nuclear power plants. Early identification of such anomalies is crucial for minimizing the risk of accidents in the future. One of the more effective techniques currently available involves measuring neutron noise and analyzing its spatial distribution throughout the reactor core [143]. For instance, Kollias et al. [130] applied ML to noise diagnostics to monitor anomalies using neutron detector measurements. Their approach involved aligning simulated data with real operational data, which enabled the detection of perturbations and facilitated fault classification and location estimation. The latest work by Mena et al. [144] explored the use of autoencoders to detect anomalies in nuclear data that could potentially be used to evaluate the operating status of a nuclear system.

In a study by Nguyen and Diab [111], a multivariate time-series ML model was utilized to predict the transient response of a typical pressurized water reactor (PWR) under a steam generator tube rupture accident (SGTR). By incorporating a Bayesian neural network (BNN), the researchers improved the accuracy of the prediction and quantified the uncertainty of the prediction results.

The Fault Monitoring and Diagnostic Monitoring System (FDDMS) enables real-time monitoring and fault analysis of nuclear reactors in different modes of operation by combining online monitoring (OLM) techniques and data-driven modeling. The core modules of the system include power transient identification, fault detection, and fault diagnosis, each of which employs ML algorithms to process and analyze large amounts of data collected from the reactor sensors. The results show that the FDDMS can effectively detect and diagnose faults under different power transient conditions. The system demonstrated the ability to recognize unknown faults and maintained high accuracy in the presence of noise [107, 145, 146].

In a study by Nguyen and Diab [111], a multivariate time-series ML model was utilized to predict the transient response of a typical pressurized water reactor (PWR) under a steam generator tube rupture accident (SGTR). By incorporating a BNN, the researchers not only improved the accuracy of the prediction but also quantified the uncertainty of the prediction results, which provides strong support for nuclear-safety decision-making.

Zubair and Akram [108], on the other hand, utilized ML methods in MATLAB to classify transient events in nuclear power plants. By collecting data using a General purpose PWR (GPWR) simulator and combining it with a classification learner application, the researchers successfully identified a wide range of transient events and significantly improved the prediction accuracy and training efficiency of the model through optimization techniques such as feature selection and different validation schemes. They [109] further explored the application of ML techniques to improve the safety and reliability of PWR. This was achieved by simulating transient events in the primary and secondary circuits and using multiple classifiers for training and validation.

In general, it may be difficult to strain new nuclear reactors in the event of an accident because of limited experience. Instead, using a virtual nuclear power plant to reproduce behaviors under various conditions and identify unknown anomalies from these behaviors, so that a rapid response can be made to avoid an accident, is a better strategy nowadays [147]. Seki et al. [147] constructed two DNN systems to support the identification of unknown anomalies and determine their causes. Specifically, they estimated the physical quantities of a nuclear power plant in a short time using an agent system and applied an anomaly recognition system to estimate the disturbance states that cause anomalies from the physical quantities. They reproduce the steady state and dynamic behavior of the actual High-Temperature Engineering Test Reactor (HTTR) under various scenarios.

#### 4.2.3 Applications in safety design

Core optimization aims to adjust the key state parameters of a reactor core, such as the power distribution, temperature field, and reactivity coefficients, to ensure safe operation and optimal performance. Typically, two major classes of optimization methods are employed: gradient descent-based methods and evolutionary algorithms (EA).

However, because most existing studies rely on external neutron simulation programs [19] to compute these state parameters, the resulting objective functions are often non-differentiable in nature. This non-differentiability can lead to issues such as vanishing gradients, which hampers the effectiveness of gradient descent-based optimization.



**4.2.3.1 PWR configuration optimization** In 2002, Sadighi et al. [92] proposed a new approach combining a continuous Hopfield Neural Network Artificial (HNNA) and Simulated Annealing (SA) Algorithm to solve the problem of optimal configuration of fuel assemblies in the core of a pressurized water reactor (PWR). The core of this approach is to utilize the parallel processing capability of neural networks and the global search capability of simulated annealing algorithms to reduce the amount of computation and increase the probability of finding an optimal solution to a problem. The Bushehr Nuclear Power Plant was used as an example, where neutron flux flattening in the core was used as an objective function to optimize the arrangement of fuel assemblies to achieve a reduction in the local PPF and an increase in energy production.

To safely optimize the core configuration, Tayefi et al. [23] used a Hopfield neural network artificial (HNNA) to guide a new approach for heuristic search. With the help of a coupled procedure of nuclear code and HNNA, a cross section database is built, neutron parameters are calculated, and then the optimal core loading pattern is found by applying the primary fuel assemblies of the VVER/1000 reactor core using the HNNA methodology based on minimizing the PPF and maximizing the  $k_{\text{eff}}$ , and the appropriate PPF and  $k_{\text{eff}}$  are obtained. In a further study [102], the fuel rods were loaded through the proposed fuel rod pattern to determine the optimum core configuration by HNNA to find the one that maximize the  $k_{\text{eff}}$ .

**4.2.3.2 BWR fuel array design** In BWR, the design of the nuclear fuel array is critical to ensure the safe operation and optimal performance of the reactor. The fuel array consists of a series of fuel rods containing different  $^{235}\text{U}$  enrichments and gadolinium concentrations, which are arranged in a square array, with some positions replaced by water channels [19]. To implement the design, Ortiz et al. [19] demonstrated a system called RENO-CC, which utilizes a multilayer state recurrent neural network (MSRNN) and a fuzzy logic system to optimize the design of the nuclear fuel array in a BWR. With this approach, the researchers were able to minimize the local PPF while maintaining the neutron  $k_{\text{inf}}$  in a given interval, thereby improving the safety and efficiency of the nuclear reactor [19]. Through a series of experiments, RENO-CC successfully designed fuel arrays to meet specific safety and performance requirements and verified their performance using the Core Master PRESTO core simulator.

**4.2.3.3 GFR core design** Because reactor designs are often complex, simulations require considerable time to perform. Kumar et al. [148] developed a genetic algorithm to determine the values of a set of nuclear reactor parameters for the design of a gas-cooled fast breeder reactor (GFR)

core, including the underlying thermo-hydraulics analysis and energy transfer. They proposed a new method of using regression spline in conjunction with GA, which instead of having to run neutronic simulations on all inputs generated by the GA module, runs simulations on a predefined set of inputs, builds a multiple regression fit to the input and output parameters, and then uses this fit to predict the output parameters of the inputs generated by GA. The reactor core is optimized for high  $^{233}\text{U}$  and  $^{239}\text{Pu}$  multiplication at the peak limit of the required power, required  $k_{\text{eff}}$  and infinite neutron multiplication factor ( $k_{\text{inf}}$ ), high fast fission factor, high thermal efficiency using the Brayton cycle to convert heat to electricity, and high fuel burnup [148].

**4.2.3.4 Single-channel design for MSR** In a molten salt reactor (MSR), the core consists of multiple fuel channels, each containing fuel and coolant, which work together to maintain the critical state of the reactor and export the heat generated by the reaction. The optimization results of a single-channel design can be used as a starting point for constructing the design of the entire reactor core, which can then be extended to the integrated design and optimization of the entire reactor system [37].

To address this problem, Turkmen et al. [37] proposed a robust methodology for the rapid design of nuclear reactor cores and explored the best-performing ML methods for predicting the characteristic parameters of the core. Furthermore, they applied the method to a hypothetical molten salt reactor channel to demonstrate its applicability. Using an estimator, they determined an optimal design for each of the nine fuel salts and estimated all the performance metrics of the design. Among all the fuel salts, the U-Pu-NaCl fuel salt has the highest conversion, largest negative feedback coefficient, and lowest fast flux [37].

**4.2.3.5 Core shape designs** Generally, a reactor core is made of industrial materials representing regular component geometries with a periodic structure; that is, one core fuel element is repeated several times to form the entire core [36]. This method produces geometrically similar fuel elements with regular shapes. For further optimization, the literature [36] also considered the optimization of the core shape from the perspective of shape design.

In the context of fixed-shape core research, Sobes et al. [36] designed a reactor core with geometrically shaped fuel and cooling channels with infinite spatial freedom as the elements. They developed an ML-based algorithm for the design and optimization of nuclear reactor cores with flexible geometries and achieved a threefold improvement in the performance metric of the peak temperature factor. This research utilized advanced manufacturing techniques, specifically additive manufacturing (AM), commonly known as 3D printing, introduced into nuclear reactor design through

the Transformational Challenge Reactor (TCR) program, which makes it possible to design arbitrary geometries for nuclear heating structures. They developed an ML-based multi-physics simulator and evaluated thousands of candidate geometries on Summit, Oak Ridge National Laboratory's leadership supercomputer. By manipulating the core geometry, the results demonstrate the possibility of smoothing the temperature distribution in a nuclear reactor core, which is typically achieved in light-water reactors by axial variable component loading and radial fuel swapping [36].

To address the challenges of redundant objectives in shielding design for compact nuclear reactors, Song et al. [149] introduced a multi-objective shielding optimization method that integrates a deep neural network, principal component analysis, and NSGA-II algorithm. By employing dimensionality reduction to eliminate redundant objectives, their method successfully balanced safety with a lightweight design, as demonstrated in both plate shielding models and the Savannah offshore nuclear reactor shielding model.

Looking ahead, it may be beneficial to explore the integration of gradient descent-based methods within deep learning frameworks, potentially through the development of differentiable surrogate models, to further enhance reactor design optimization.

## 5 ML-based reactor physics: future challenges and directions

Although ML techniques have made significant strides in reactor physics, they continue to face substantial challenges. The next theoretical or practical advancements are uncertain. However, we identified several challenging topics emerging in the literature that highlight key areas of difficulty and suggest potential directions for future research. These challenges serve as a foundation for further exploration and help us contemplate the future trajectory of ML applications in reactor physics.

### 5.1 Overcoming theoretical difficulties

In the foundational aspects of reactor physics, as discussed in Sect. 2, the key governing equations and essential state parameters are introduced. The governing equations include the neutron transport or neutron diffusion equation, point kinetics equation, and burnup equations. The important state parameters in practical applications include the multiplication factor, reaction cross section, neutron flux, and power rate distribution. These governing equations form the cornerstone of the deterministic approach in reactor physics. Based on insights from the literature, two primary directions emerge for addressing the theoretical challenges in this field: method-based and model-based challenges. These directions

represent critical avenues for advancing the resolution of complex problems in reactor physics.

#### 5.1.1 Method-based challenges

The frontier ML prediction methodology is represented in reactor physics using DL. The DNN architecture derived from DL is also used as a fundamental architecture in many applications.

It is well known that in ML methods, especially supervised or semi-supervised learning, the quality of the data has a significant impact on the results. Therefore, one of the challenges is the selection of a particular sampling method. In reactor physics, which usually involves a high-dimensional parameter space, traditional sampling methods are inefficient. During the research process, suitable sampling algorithms can facilitate the training process and provide better approximations [150], which is one of the future research directions.

The core of an NN is the selection of the loss function and the structure of the data grid, which can be further investigated in these two aspects. For example, during the research of MSPCNN for seamless encoding of multi-fidelity data [131], the adaptability and computational efficiency are high, but for this class of networks, it is easy to amplify the error in scenes with limited spatial correlations. Therefore, customizing the loss function to balance the fidelity and reduce the error will be an extension of this problem. In addition, in real-world applications, it is often necessary to model unstructured or even adaptive grids, where the number and arrangement of grids can be dynamically varied to better capture the phenomena or optimize the computational resources [131].

Breakthroughs can also be achieved in terms of the scale of the problem. The acquisition of high-resolution, high-fidelity data is a significant challenge for larger and more complex problems. The generation of high-fidelity data, such as those obtained using the statistical Monte Carlo method, is particularly resource intensive. The current mainstream approach consists of fitting high-fidelity data from low-fidelity data with error predictions; for example, the literature [127] shows how to augment the running simulation of a boiling water reactor (BWR) with the help of ML in combination with traditional simulation techniques. This complementary approach is only in its infancy and is limited to small reactor problems presented in the literature [72]. The enhancement of the simulation of high-dimensional problems with the aid of ML for large-scale problems is still under research [7]. This approach may even be extended to the study of other types of reactors. This is necessary; removing the uncertainty approach to simulation, although for realistic reactors, it is possible to obtain operational data, how the data noise is handled should also be considered;

in addition, not every demanded parameter has been pre-measured [7, 72].

Finally, the topic can be considered as an improvement in the algorithm architecture. Specifically, it involves changes in the existing network structure. The DL-based PINN method and its variants are particularly used in the review of the main text, which are known for their efficient performance and low mesh dependency. If the Transformer architecture could be integrated into the PINN architecture [131], or a new auxiliary ML model inspired by the Transformer could be created, completely different results could be obtained.

### 5.1.2 Model-based challenges

One of the important concerns of the industry regarding theoretical models is their interpretability. In some cases, reactor operators may be more interested in the input parameters that led to the observation or state of interest. Therefore, parameter identification (PI) is another intriguing task [10]. Therefore, a previous study [10] established a digital twin based on non-intrusive modeling and ML methods for the inverse problems of PI, achieving good performance in terms of accurate prediction in a short period. Non-intrusive modeling refers to a modeling approach that does not require the modification of the original (forward) model or direct intervention in the physical process. The model can directly utilize the physical model as an input, which retains some physical meaning and improves its interpretability. Another issue is uncertainty quantification [96]. The nuclear reactor itself is a complex system consisting of multi-physics, multi-scale, and for different scales, there may be different parameters, assumptions, and models. To more accurately and comprehensively consider the interpretability of the model, the literature points toward real-time inference and digital-twin-enabled deployment as an important future direction [137]. Stewart et al. [142] investigated the appropriateness of different ML methods for final implementation by assessing the pros and cons of each method in terms of accuracy, access, development, efficiency, and transfer learning approaches. The authors also investigated the explainability and interpretability, assessed the model performance on live data streams, and identified strategies for model verification.

To improve the applicability and reliability of the model, another critical issue is the generalization of the model, which is also known as the robustness of the model. This is also a solution strategy for multi-scale problems. In most studies, ML methods have been applied to specific reactors. Therefore, the specificity of ML methods for data is a problem to be considered; in other words, a generalization model needs to be found to reduce the dependence on data

or even provide a better model without knowing the data in advance [7, 48].

## 5.2 Improving implementation aspects

From the perspective of real industrial applications, the addition of a digital twin can remarkably improve simulation efficiency. Digital twins [10], as stated by Marguet [15], as online agents continuously assimilate models and experimental measurements, which are already known to be faster than real-time processes, should be further investigated. Digital twins can be used along with new data assimilation methods and ML techniques that can be essential in the entire life cycle of a reactor core.

In terms of deployment, robustness against measurement degradation and data drift remains an important research direction. Sensors in nuclear reactors may be degraded by environmental influences or long-term use. ML methods can help capture the characteristics of the degraded state of the sensors; however, the challenge lies in how to accurately identify and process them to ensure the reliability and accuracy of monitoring and controlling the behavior of nuclear reactors.

In addition, strengthening accident handling capabilities with the aid of ML through nuclear reactor dynamics equations [151] can effectively enhance nuclear reactor safety. Nuclear reactor accident handling is a complex process that requires consideration of various factors and uncertainties, including how to quantify the uncertainty well, how to enhance the anomaly monitoring capability, and how to improve the prediction performance.

Symbolic language conversion is a relatively new topic. ML methods usually use mathematical models and ML algorithms for modeling and analysis, which makes it difficult for humans to understand the model's results. To integrate theory with practice, research is needed on how to transform the results of ML models into a human-understandable symbolic language that can better support decisions and applications.

Finally, handling noisy measurement data remains challenging [7, 144]. Accurate observation of noise is critical for model predictions and system monitoring. ML methods can help improve the accuracy of noise observations, but the challenge of efficiently processing noisy data and differentiating between real signals and noise needs to be addressed.

## 6 Conclusion

This review provides an in-depth study of the research directions and content of the application of ML methods to nuclear reactor physics since their development. Currently, the application of ML methods in reactor physics focuses on theoretical and applied directions. On one hand, the

research begins with the efficiency of solving governing equations and the efficiency of predicting reaction state parameters, the former with the help of DL technology, in which the PINN algorithm and its variants have yielded excellent results. The latter, on the other hand, focuses on the multiplication factor, neutron cross section, and neutron flux, and mainly focuses on reducing the amount of computation while maintaining the accuracy of the solution, i.e., an innovative approach that unifies efficiency and accuracy. In terms of the solution of nuclear reactor problems based on the ML methods, it can be seen as a response to the equations and parameters in Sect. 2 on how to solve practical problems. Some of the difficult problems in reactor physics can be developed in three important areas: steady state, transient state, and burnup. Steady-state problems consider the prediction of performance, temperature field, and core power, including the estimation of the power peaking factor, and provide advancements mainly for areas such as core design. The transient problem is concerned with reactor behavior monitoring and safety analysis, particularly how to respond quickly and make safe decisions under accident conditions. Burnup is considered from the perspective of fuel composition, burnup distribution, and other reaction environments. Furthermore, advancements in nuclear engineering are increasingly driven by the simulation, regulation, and design of nuclear reactors, effectively bridging the theoretical challenges discussed in the previous chapter with practical applications. ML methods play crucial roles in data generation, anomaly identification, and noise management. Additionally, concepts such as data assimilation, agent-based modeling, and digital twin technology are being incorporated into practical applications, serving as prime examples of how ML methods can be seamlessly integrated into complex nuclear systems. These developments highlight the potential of ML to enhance the safety and efficiency of nuclear reactor operations.

In conclusion, the application of ML methods in nuclear reactor physics holds significant potential for further development in this field. Theoretically, there is room for enhancing ML methods and structures, particularly by improving the interpretability and generalization of models. From a broader perspective, challenges remain in areas such as optimizing simulation performance, accelerating anomaly detection, refining accident handling, and enhancing safety designs in industrial settings. Additionally, the industry faces substantial challenges, including the need for objective exclusion, expansion of digital twin technology, and pursuit of better data parsimony. Furthermore, it should be emphasized that machine learning in the coupling of reactor physics and thermo-hydraulics is still an important topic that requires further research and review. Addressing these challenges is crucial for

advancing the integration of ML in nuclear reactor physics and engineering.

## References

1. N. Cho, Fundamentals and recent developments of reactor physics methods. *Nucl. Eng. Technol.* **37**, 25–78 (2005)
2. N. Schunck, D. Regnier, Theory of nuclear fission. *Prog. Part. Nucl. Phys.* **125**, 103963 (2022). <https://doi.org/10.1016/j.pnpnp.2022.103963>
3. W.M. Stacey, *Nuclear reactor physics*. (John Wiley & Sons, 2018)
4. D.A. Arostegui, M. Holt, Advanced nuclear reactors: technology overview and current issues. Technical Report R45706, U.S. Congressional research service, Washington, DC (2019). <https://crsreports.congress.gov/product/pdf/R/R45706>
5. H. Sekimoto, *Nuclear Reactor Theory* (COE-INES, Japan, 2007)
6. T. Zhang, D. She, Q. Zhang et al., Editorial: reactor physics: methods and applications. *Front. Energy Res.* **10**, 928836 (2022). <https://doi.org/10.3389/fenrg.2022.928836>
7. IAEA, Fundamental safety principles. IAEA Safety Standards Series No. SF-1, International Atomic Energy Agency, Vienna, 2006.
8. G. Kessler, A. Vesper, Some facts about neutron and reactor physics. In: *The Risks of Nuclear Energy Technology*, (Springer, Berlin, 2014), pp. 11–32. [https://doi.org/10.1007/978-3-642-55116-1\\_2](https://doi.org/10.1007/978-3-642-55116-1_2)
9. H. Gong, Data assimilation with reduced basis and noisy measurement: applications to nuclear reactor cores. Ph.D. thesis, Sorbonne Université, 2018.
10. H. Gong, S. Cheng, Z. Chen et al., Data-enabled physics-informed machine learning for reduced-order modeling digital twin: application to nuclear reactor physics. *Nucl. Sci. Eng.* **196**, 668–693 (2022). <https://doi.org/10.1080/00295639.2021.2014752>
11. A.M. Weinberg, G. Caglioti, K. Sahai et al., Nuclear reactor physics. II *Nuovo Cimento* **4**, 1278–1323 (1956). <https://doi.org/10.1007/BF02744348>
12. A.M. Weinberg, Current status of nuclear reactor theory. *Am. J. Phys.* **20**, 401–412 (1952). <https://doi.org/10.1119/1.1933268>
13. G.I. Bell, S. Glasstone, *Nuclear Reactor Theory* (US Atomic Energy Commission, Washington, DC, 1970)
14. J.J. Duderstadt, L.J. Hamilton, *Nuclear Reactor Analysis* (Wiley, 1976)
15. S. Marguet, *The Physics of Nuclear Reactors* (Springer, Cham, 2017)
16. W. Kim, J. Park, T. Kozlowski et al., Comparative neutronics analysis of DIMPLe S06 criticality benchmark with contemporary reactor core analysis computer code systems. *Sci. Technol. Nucl. Install.* **2015**, 180979 (2015). <https://doi.org/10.1155/2015/180979>
17. J.J. Ortiz, I. Requena, Using neural networks to predict core parameters in a boiling water reactor. *Nucl. Sci. Eng.* **143**, 254–267 (2003). <https://doi.org/10.13182/NSE03-A2334>
18. J.J. Ortiz, I. Requena, Using a multi-state recurrent neural network to optimize loading patterns in BWRs. *Ann. Nucl. Energy* **31**, 789–803 (2004). <https://doi.org/10.1016/j.anucene.2003.11.001>
19. J.J. Ortiz, A. Castillo, J.L. Montes et al., Nuclear fuel lattice optimization using neural networks and a fuzzy logic system. *Nucl. Sci. Eng.* **162**, 148–159 (2009). <https://doi.org/10.13182/nse162-148>



20. T. Kozłowski, D. Lee, T.J. Downar, The use of an artificial neural network for on-line prediction of pin-cell discontinuity factors in PARCS. *Proc. PHYSOR 2004* (2004)
21. I.H. Bae, M.G. Na, Y.J. Lee et al., Calculation of the power peaking factor in a nuclear reactor using support vector regression models. *Ann. Nucl. Energy* **35**, 188–195 (2008). <https://doi.org/10.1016/j.anucene.2008.09.004>
22. K. Trontl, D. Pevec, T. Šmuc, Machine learning of the reactor core loading pattern critical parameters. *Sci. Technol. Nucl. Install.* **2008**, 695153 (2008). <https://doi.org/10.1155/2008/695153>
23. S. Tayefi, A. Pazirandeh, Evaluation of applying axial variation of enrichment distribution method and radial variation of enrichment distribution in VVER/1000 reactor using a Hopfield neural network to optimize fuel management. *Prog. Nucl. Energy* **64**, 47–53 (2013). <https://doi.org/10.1016/j.pnucene.2013.01.001>
24. A. Pirouzmand, M.K. Dehdashti, Estimation of relative power distribution and power peaking factor in a VVER-1000 reactor core using artificial neural networks. *Prog. Nucl. Energy* **85**, 17–27 (2015). <https://doi.org/10.1016/j.pnucene.2015.06.001>
25. M. Gomez Fernandez, A. Tokuhito, K. Welter et al., Nuclear energy system's behavior and decision making using machine learning. *Nucl. Eng. Des.* **324**, 27–34 (2017). <https://doi.org/10.1016/j.nucengdes.2017.08.020>
26. S.O. Starkov, Y.N. Lavrenkov, Prediction of temperature field of moderator of heavy-water reactor based on cellular neural network. *Izv. Vyssh. Uchebn. Zaved. Yad. Energ.* **1**, 94–106 (2017). <https://doi.org/10.26583/npe.2017.1.09>
27. Y. Zeng, J. Liu, K. Sun et al., Machine learning based system performance prediction model for reactor control. *Ann. Nucl. Energy* **113**, 20–29 (2018). <https://doi.org/10.1016/j.anucene.2017.11.014>
28. T. Tagaris, G. Ioannou, M. Sdraka et al., Putting together wavelet-based scaleograms and convolutional neural networks for anomaly detection in nuclear reactors. *Proc. Adv. Artif. Intell.* 237–243 (2020). <https://doi.org/10.1145/3369114.3369121>
29. E. Bamidele, A. Cherezov, S. Dzianisau et al., Machine learning of LWR spent nuclear fuel assembly decay heat measurements. *Nucl. Eng. Technol.* **53**, 3010–3018 (2021). <https://doi.org/10.1016/j.net.2021.05.037>
30. J.J. Berry, G.G. Gil-Delgado, A.G.S. Osborne, Classification of group structures for a multigroup collision probability model using machine learning. *Ann. Nucl. Energy* **160**, 108367 (2021). <https://doi.org/10.1016/j.anucene.2021.108367>
31. Z. Chen, L. Liu, L. Mu, Solving the linear transport equation by a deep neural network approach. *arXiv:2102.09157* (2021). <http://arxiv.org/abs/2102.09157>
32. S.B. Alam, J. Daniell, A. Alajo et al., Physics-informed multi-stage deep learning framework development for state-based reactor power prediction. In Review (2023). <https://doi.org/10.21203/rs.3.rs-3650233/v1>
33. Đ Petrović, K. Mikityuk, Machine learning based methodology for assessment of Doppler reactivity of sodium cooled fast reactor. *ASME J. Nucl. Radiat. Sci.* **7**, 041008 (2021). <https://doi.org/10.1115/1.4050216>
34. Y. Xie, Y. Wang, Y. Ma, Z. Wu, Neural network based deep learning method for multi-dimensional neutron diffusion problems with novel treatment to boundary. *J. Nucl. Eng.* **2**, 533–552 (2021). <https://doi.org/10.3390/jne2040036>
35. S. Chen, J. Zhou, X. Cai et al., Machine learning approaches to equilibrium burnup analysis for Molten Salt Reactor. *Ann. Nucl. Energy* **192**, 109995 (2023). <https://doi.org/10.1016/j.anucene.2023.109995>
36. V. Sobes, B. Hiscox, E. Popov et al., AI-based design of a nuclear reactor core. *Sci. Rep.* **11**, 19646 (2021). <https://doi.org/10.1038/s41598-021-98037-1>
37. M. Turkmen, G.J.Y. Chee, K.D. Huff, Machine learning application to single channel design of molten salt reactor. *Ann. Nucl. Energy* **161**, 108409 (2021). <https://doi.org/10.1016/j.anucene.2021.108409>
38. H. Gong, S. Cheng, Z. Chen et al., An efficient digital twin based on machine learning SVD autoencoder and generalised latent assimilation for nuclear reactor physics. *Ann. Nucl. Energy* **179**, 109431 (2022). <https://doi.org/10.1016/j.anucene.2022.109431>
39. K. Prantikos, L.H. Tsoukalas, A. Heifetz, Physics-informed neural network solution of point kinetics equations for a nuclear reactor digital twin. *Energies* **15**, 7697 (2022). <https://doi.org/10.3390/en15207697>
40. M. Raissi, P. Perdikaris, G.E. Karniadakis, Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *J. Comput. Phys.* **378**, 686–707 (2019). <https://doi.org/10.1016/j.jcp.2018.10.045>
41. X. Geng, D. Chen, J. Yu et al., Physics-informed neural network for solving neutron transport equation with differential order transformation and Fourier feature. *J. Comput. Phys.* **546**, 114519 (2026). <https://doi.org/10.1016/j.jcp.2025.114519>
42. Q. Dong, P. Lei, F. Fan, Solving multi-dimensional neutron diffusion equation using deep machine learning technology based on PINN model. *Nucl. Power Eng.* **43**, 1–8 (2022). <https://doi.org/10.13832/j.jnpe.2022.02.0001>
43. M.H. Elhareef, Z. Wu, Physics-informed neural network method and application to nuclear reactor calculations: a pilot study. *Nucl. Sci. Eng.* **197**, 601–622 (2023). <https://doi.org/10.1080/00295639.2022.2123211>
44. B. Whewell, R.G. McClarren, Data reduction in deterministic neutron transport calculations using machine learning. *Ann. Nucl. Energy* **176**, 109276 (2022). <https://doi.org/10.1016/j.anucene.2022.109276>
45. J. Wang, X. Peng, Z. Chen et al., Surrogate modeling for neutron diffusion problems based on conservative physics-informed neural networks with boundary conditions enforcement. *Ann. Nucl. Energy* **176**, 109234 (2022). <https://doi.org/10.1016/j.anucene.2022.109234>
46. Y. Xie, Y. Wang, Y. Ma, Boundary dependent physics-informed neural network for solving neutron transport equation. *Ann. Nucl. Energy* **195**, 110181 (2024). <https://doi.org/10.1016/j.anucene.2023.110181>
47. K. Prantikos, S. Chatzidakis, L.H. Tsoukalas et al., Physics-informed neural network with transfer learning (TL-PINN) based on domain similarity measure for prediction of nuclear reactor transients. *Sci. Rep.* **13**, 16840 (2023). <https://doi.org/10.1038/s41598-023-43325-1>
48. Q.H. Yang, Y. Yang, Y.T. Deng et al., Physics-constrained neural network for solving discontinuous interface K-eigenvalue problem with application to reactor physics. *Nucl. Sci. Tech.* **34**, 161 (2023). <https://doi.org/10.1007/s41365-023-01313-0>
49. S. Cuomo, V.S. Di Cola, F. Giampaolo et al., Scientific machine learning through physics-informed neural networks: where we are and what's next. *J. Sci. Comput.* **92**, 88 (2022). <https://doi.org/10.1007/s10915-022-01939-z>
50. B. Whewell, R.G. McClarren, Reduced models for nuclear data in transport problems. in: *Proceedings of The International Conference on Mathematics and Computational Methods Applied to Nuclear Science and Engineering (M&C 2021)*, 2021.
51. X. Zhao, R.K. Salko, K. Shirvan, Improved departure from nucleate boiling prediction in rod bundles using a physics-informed machine learning-aided framework. *Nucl. Eng. Des.* **374**, 111084 (2021). <https://doi.org/10.1016/j.nucengdes.2021.111084>
52. T. Kircher, F.A. Döppel, M. Votsmeier, Global reaction neural networks with embedded stoichiometry and thermodynamics



- for learning kinetics from reactor data. *Chem. Eng. J.* **481**, 149863 (2024). <https://doi.org/10.1016/j.cej.2024.149863>
53. Q.A. Huhn, M.E. Tano, J.C. Ragusa, Physics-informed neural network with Fourier features for radiation transport in heterogeneous media. *Nucl. Sci. Eng.* **197**, 2484–2497 (2023). <https://doi.org/10.1080/00295639.2023.2184194>
  54. H.M. Park, J.H. Lee, K.D. Kim, Wall temperature prediction at critical heat flux using a machine learning model. *Ann. Nucl. Energy* **141**, 107334 (2020). <https://doi.org/10.1016/j.anucene.2020.107334>
  55. D. Neudecker, O. Cabellos, A.R. Clark et al., Informing nuclear physics via machine learning methods with differential and integral experiments. *Phys. Rev. C* **104**, 034611 (2021). <https://doi.org/10.1103/PhysRevC.104.034611>
  56. D. Neudecker, M. Grosskopf, M. Herman et al., Enhancing nuclear data validation analysis by using machine learning. *Nucl. Data Sheets* **167**, 36–60 (2020). <https://doi.org/10.1016/j.nds.2020.07.002>
  57. H. Özdoğan, Estimation of (n, p) reaction cross sections at  $14.5 \pm 0.5$  MeV neutron energy by using artificial neural network. *Appl. Radiat. Isot.* **170**, 109584 (2021). <https://doi.org/10.1016/j.apradiso.2020.109584>
  58. H. Özdoğan, Y.A. Üncü, M. Sekerci et al., Estimations for ( $n, \alpha$ ) reaction cross sections at around 14.5 MeV using Levenberg-Marquardt algorithm-based artificial neural network. *Appl. Radiat. Isot.* **192**, 110609 (2023). <https://doi.org/10.1016/j.apradiso.2022.110609>
  59. W.B. He, Q.F. Li, Y.G. Ma et al., Machine learning in nuclear physics at low and intermediate energies. *Sci. China Phys. Mech. Astron.* **66**(8), 282001 (2023). <https://doi.org/10.1007/s11433-023-2116-0>
  60. D.M. Van Patter, Neutron transport theory. *J. Frankl. Inst.* **264**, 251–252 (1957). [https://doi.org/10.1016/0016-0032\(57\)90992-4](https://doi.org/10.1016/0016-0032(57)90992-4)
  61. A.M.G. Cox, S.C. Harris, E.L. Horton et al., Multi-species neutron transport equation. *J. Stat. Phys.* **176**, 425–455 (2019). <https://doi.org/10.1007/s10955-019-02307-2>
  62. S.I. Heizler, Asymptotic telegrapher's equation (P1) approximation for the transport equation. *Nucl. Sci. Eng.* **166**, 17–35 (2010). <https://doi.org/10.13182/nse09-77>
  63. J. Berg, K. Nyström, A unified deep artificial neural network approach to partial differential equations in complex geometries. *Neurocomputing* **317**, 28–41 (2018). <https://doi.org/10.1016/j.neucom.2018.06.056>
  64. W. Wang, Y. Li, J. Qin et al., Analytical solution study on transient neutron transport in homogeneous bare reactor based on neutron telegraph equation. *Nucl. Power Eng.* **45**, 1–5 (2024). <https://doi.org/10.13832/j.jnpe.2024.02.0042>
  65. A.F. Henry, The application of reactor kinetics to the analysis of experiments. *Nucl. Sci. Eng.* **3**, 52–70 (1958). <https://doi.org/10.13182/NSE58-1>
  66. E. Schiassi, M. De Florio, B.D. Ganapol et al., Physics-informed neural networks for the point kinetics equations for nuclear reactor dynamics. *Ann. Nucl. Energy* **167**, 108833 (2022). <https://doi.org/10.1016/j.anucene.2021.108833>
  67. E.E. Lewis, W.F. Miller, Computational methods of neutron transport (1984)
  68. S. Huang, W. Feng, C. Tang et al., Partial differential equations meet deep neural networks: a survey (2022). <http://arxiv.org/abs/2211.05567>
  69. A. Vivancos, R. Miró, T. Barrachina et al., Deterministic neutron transport and burnup code coupling assessment. *Ann. Nucl. Energy* **198**, 110291 (2024). <https://doi.org/10.1016/j.anucene.2023.110291>
  70. A. Hébert, *Applied Reactor Physics*, 3rd edn. (Presses Internationales Polytechnique, Québec, 2020)
  71. Q. Zhang, J. Zhang, L. Liang et al., A deep learning based surrogate model for estimating the flux and power distribution solved by diffusion equation. *EPJ Web Conf.* **247**, 03013 (2021). <https://doi.org/10.1051/epjconf/202124703013>
  72. M.R. Oktavian, J. Nistor, J.T. Gruenwald et al., Preliminary development of machine learning-based error correction model for low-fidelity reactor physics simulation. *Ann. Nucl. Energy* **187**, 109788 (2023). <https://doi.org/10.1016/j.anucene.2023.109788>
  73. A. Pirouzmand, K. Hadad, K.Y. Suh, Analog computing for a new nuclear reactor dynamic model based on a time-dependent second order form of the neutron transport equation. *Nucl. Eng. Technol.* **43**, 243–256 (2011). <https://doi.org/10.5516/NET.2011.43.3.243>
  74. L. Cao, Z. Xie, Y. Li, *Physical analysis of modern nuclear reactors*. (China Atomic Energy Press, Beijing, 2017)
  75. D. Liu, X. Wang, B. Zhang et al., Differential transform order theory for solving neutron transport equation by deep learning method. *At. Energy Sci. Technol.* (in Chinese) **57**, 946–959 (2023). <https://doi.org/10.7538/yzk.2023.youxian.0002>
  76. R.G. Türeç, Machine learning applications to the one-speed neutron transport problems. *Cumhuriyet Sci. J.* **43**, 726–738 (2022). <https://doi.org/10.17776/cs.1163514>
  77. M. H. Elhareef, Z. Wu, Y. Ma, Physics-informed deep learning neural network solution to the neutron diffusion model. *Proc. Int. Conf. Math. Comput. Methods Appl. Nucl. Sci. Eng. (M&C)* (2021)
  78. M. H. Elhareef, Z. Wu, Extension of the PINN diffusion model to k-eigenvalue problems. *Proc. Int. Conf. Phys. React. (PHYSOR)* (2022). <https://doi.org/10.13182/PHYSOR22-37488>
  79. R.D.E. Gatchalian, P.V. Tsvetkov, Traditional machine learning methods in predicting the physics of subcritical systems in source-equilibrium. *Ann. Nucl. Energy* **201**, 110413 (2024). <https://doi.org/10.1016/j.anucene.2024.110413>
  80. H.G. Kim, S.H. Chang, B.H. Lee, Pressurized water reactor core parameter prediction using an artificial neural network. *Nucl. Sci. Eng.* **113**, 70–76 (1993). <https://doi.org/10.13182/NSE93-A23994>
  81. C. Ren, J. Liu, X. Yang, Multiplication factor prediction feasibility study for the BEAVRS core based on the LSTM algorithm. *Proc. 29th Int. Conf. Nucl. Eng.* (2022). <https://doi.org/10.1115/ICONE29-90164>
  82. X. Bei, Y. Dai, K. Yu et al., Three-dimensional surrogate model based on back-propagation neural network for key neutronics parameters prediction in Molten Salt Reactor. *Energies* **16**, 4044 (2023). <https://doi.org/10.3390/en16104044>
  83. N. Martin, Z. Prince, V. Labouré et al., Deep learning for multi-group cross-section representation in two-step core calculations. *Nucl. Sci. Eng.* **197**, 1406–1435 (2023). <https://doi.org/10.1080/00295639.2022.2159220>
  84. P. Vicente-Valdez, L. Bernstein, M. Fratoni, Nuclear data evaluation augmented by machine learning. *Ann. Nucl. Energy* **163**, 108596 (2021). <https://doi.org/10.1016/j.anucene.2021.108596>
  85. K. Tan, M. Liu, C. Wei, Development of cross-section calculation module for high-temperature gas-cooled reactor engineering simulator system using an optimal model tree algorithm. *Ann. Nucl. Energy* **184**, 109683 (2023). <https://doi.org/10.1016/j.anucene.2023.109683>
  86. M. Ravichandran, C.A. Gentry, M. Bucci, Investigation into the use of machine learning assisted prediction of nodal parameters for reduced order neutronic simulation models. *Proc. Int. Conf. Math. Comput. Methods Appl. Nucl. Sci. Eng. (M&C)* (2021). <https://www.osti.gov/servlets/purl/1829201>
  87. I.E. Ivanov, S.A. Bychkov, N.A. Grushin et al., Applying machine learning and neural networks to approximate libraries of constants in a rew-group library of neutronic constants to

- simulate RBMK-1000. *Phys. At. Nucl.* **85**, 1400–1410 (2022). <https://doi.org/10.1134/S1063778822080166>
88. X. Sun, Z. Wei, D. Wang et al., Study of (n,2n) reaction cross section of fission product based on neural network and decision tree model. *At. Energy Sci. Technol. (in Chinese)* **57**, 798–804 (2023). <https://doi.org/10.7538/yzk.2023.youxian.0049>
89. Z. Li, J. Sun, C. Wei et al., A new Cross-section calculation method in HTGR engineering simulator system based on Machine learning methods. *Ann. Nucl. Energy* **145**, 107553 (2020). <https://doi.org/10.1016/j.anucene.2020.107553>
90. B. Leniau, B. Mouginot, N. Thiollie et al., A neural network approach for burn-up calculation and its application to the dynamic fuel cycle code CLASS. *Ann. Nucl. Energy* **81**, 125–133 (2015). <https://doi.org/10.1016/j.anucene.2015.03.035>
91. G.P.A. Nobre, D.A. Brown, S.J. Hollick et al., Novel machine-learning method for spin classification of neutron resonances. *Phys. Rev. C* **107**, 034612 (2023). <https://doi.org/10.1103/PhysRevC.107.034612>
92. M. Sadighi, S. Setayeshi, A.A. Salehi, PWR fuel management optimization using neural networks. *Ann. Nucl. Energy* **29**, 41–51 (2002). [https://doi.org/10.1016/S0306-4549\(01\)00024-X](https://doi.org/10.1016/S0306-4549(01)00024-X)
93. J. Berry, P. Romano, A. Osborne, Upsampling Monte Carlo reactor simulation tallies in depleted LWR assemblies fueled with LEU and HALEU using a convolutional neural network. *AIP Adv.* **14**, 015004 (2024). <https://doi.org/10.1063/5.0169833>
94. M.G. Lysenko, H.-I. Wong, G.I. Maldonado, Predicting neutron diffusion eigenvalues with a query-based adaptive neural architecture. *IEEE Trans. Neural Netw.* **10**, 790–800 (1999). <https://doi.org/10.1109/72.774221>
95. X. Li, K. Cheng, T. Huang, S. Tan, Research on neutron diffusion equation and nuclear thermal coupling method based on gradient updating finite volume method. *Ann. Nucl. Energy* **195**, 110158 (2024). <https://doi.org/10.1016/j.anucene.2023.110158>
96. Y. Yang, H. Gong, Q. He et al., On the uncertainty analysis of the data-enabled physics-informed neural network for solving neutron diffusion eigenvalue problem. *Nucl. Sci. Eng.* **198**, 1075–1096 (2024). <https://doi.org/10.1080/00295639.2023.2236840>
97. F. Khoshahval, S. Yum, H.C. Shin et al., Smart sensing of the axial power and offset in NPPs using GMDH method. *Ann. Nucl. Energy* **121**, 77–88 (2018). <https://doi.org/10.1016/j.anucene.2018.07.007>
98. C.V. Anghel, B.P. Bromley, A.A. Prudil et al., Preliminary evaluation of the LASSO method for prediction of the relative power density distribution in mixed oxide (Pu, DU)O<sub>2</sub> fuel pellets. *J. Nucl. Eng. Radiat. Sci.* **8**, 021502 (2022). <https://doi.org/10.1115/1.4050767>
99. J. Daniell, K. Kobayashi, S. Alam et al., Multi-stage neural network framework for probabilistic-to-continuous predictions. In: *Proc. 13th Nuclear Plant Instrumentation, Control and Human-Machine Interface Technologies (NPIC and HMIT 2023)*, 1278–1287 (2023)
100. J. Wan, Q.F. Jiang, L.T. Liao et al., A neural-network based variable universe fuzzy control method for power and axial power distribution control of large pressurized water reactors. *Ann. Nucl. Energy* **175**, 109241 (2022). <https://doi.org/10.1016/j.anucene.2022.109241>
101. A. Hedayat, H. Davilu, A.A. Barfrosh et al., Estimation of research reactor core parameters using cascade feed forward artificial neural networks. *Prog. Nucl. Energy* **51**, 709–718 (2009). <https://doi.org/10.1016/j.pnucene.2009.03.004>
102. S. Tayefi, A. Pazirandeh, Using Hopfield neural network to optimize fuel rod loading patterns in VVER/1000 reactor by applying axial variation of enrichment distribution. *Appl. Soft Comput.* **21**, 501–508 (2014). <https://doi.org/10.1016/j.asoc.2014.03.018>
103. D.A.P. Palma, A.S. Martinez, F.C. da Silva, The calculation of the reactivity by the telegraph equation. *Ann. Nucl. Energy* **110**, 31–35 (2017). <https://doi.org/10.1016/j.anucene.2017.06.017>
104. K. Moshkbar-Bakhshayesh, M.B. Ghofrani, Transient identification in nuclear power plants: a review. *Prog. Nucl. Energy* **67**, 23–32 (2013). <https://doi.org/10.1016/j.pnucene.2013.03.017>
105. S. Choi, M. Garrouste, U. Baker et al., Development of learning-based model predictive control framework for SMRs. Technical Report, NE/8975-2021-011-00, University of Michigan (2021). <https://doi.org/10.7302/3787>
106. M.-G. Park, H.-C. Shin, Reactor power shape synthesis using Group Method of Data Handling. *Ann. Nucl. Energy* **72**, 467–470 (2014). <https://doi.org/10.1016/j.anucene.2014.06.010>
107. M. Mendoza, P.V. Tsvetkov, An intelligent fault detection and diagnosis monitoring system for reactor operational resilience: power transient identification. *Prog. Nucl. Energy* **156**, 104529 (2023). <https://doi.org/10.1016/j.pnucene.2022.104529>
108. M. Zubair, Y. Akram, Utilizing MATLAB machine learning models to categorize transient events in a nuclear power plant using generic pressurized water reactor simulator. *Nucl. Eng. Des.* **415**, 112698 (2023). <https://doi.org/10.1016/j.nucengdes.2023.112698>
109. M. Zubair, Y. Akram, Enhancement in the safety and reliability of Pressurized Water reactors using Machine Learning approach. *Ann. Nucl. Energy* **201**, 110448 (2024). <https://doi.org/10.1016/j.anucene.2024.110448>
110. A. Gurgun, N.T. Dinh, Development and assessment of a reactor system prognosis model with physics-guided machine learning. *Nucl. Eng. Des.* **398**, 111976 (2022). <https://doi.org/10.1016/j.nucengdes.2022.111976>
111. T.C.H. Nguyen, A. Diab, Using machine learning to forecast and assess the uncertainty in the response of a typical PWR undergoing a steam generator tube rupture accident. *Nucl. Eng. Technol.* **55**, 3423–3440 (2023). <https://doi.org/10.1016/j.net.2023.05.025>
112. J. Bae, G. Kim, S.J. Lee, Real-time prediction of nuclear power plant parameter trends following operator actions. *Expert Syst. Appl.* **186**, 115848 (2021). <https://doi.org/10.1016/j.eswa.2021.115848>
113. K. Jareteg, P. Vinai, C. Demazière, Fine-mesh deterministic modeling of PWR fuel assemblies: proof-of-principle of coupled neutronic/thermal-hydraulic calculations. *Ann. Nucl. Energy* **68**, 247–256 (2014). <https://doi.org/10.1016/j.anucene.2013.12.019>
114. Q.X. Xie, W. Li, C.R. Guan et al., Development of 3D transient neutronics and thermal-hydraulics coupling procedure and its application to a fuel pin analysis. *Nucl. Eng. Des.* **404**, 112164 (2023). <https://doi.org/10.1016/j.nucengdes.2023.112164>
115. J. Zhang, X. Liu, J. Xiong et al., Rapid prediction of multi-physics coupling in heat pipe reactor based on neural network. *At. Energy Sci. Technol. (in Chinese)* **58**(6), 1218–1225 (2024). <https://doi.org/10.7538/yzk.2023.youxian.0762>
116. Y. Che, J. Yurko, P. Seurin et al., Machine learning-assisted surrogate construction for full-core fuel performance analysis. *Ann. Nucl. Energy* **168**, 108905 (2022). <https://doi.org/10.1016/j.anucene.2021.108905>
117. M. Aghili Nasr, L. Loi, S. Riva et al., Enhancing multi-physics modeling in new-generation nuclear reactors using machine learning: implementing Gaussian process regression for updating cross sections (2024). <https://doi.org/10.2139/ssrn.5045576>
118. H. Bao, N. Dinh, L. Lin, Machine learning in nuclear thermal hydraulics, Part 2: opportunities and perspectives. Technical Report, INL/CON-20-59191-Rev 000, Idaho National Laboratory (INL), Idaho Falls (2020). <https://www.osti.gov/biblio/2203929>
119. P. Maria, Higher-order Chebyshev rational approximation method and application to burnup equations. *Nucl. Sci. Eng.* **182**, 297–318 (2016). <https://doi.org/10.1318/NSE15-26>

120. A. Yamamoto, M. Tatsumi, N. Sugimura, Numerical solution of stiff burnup equation with short half lived nuclides by the Krylov Subspace method. *J. Nucl. Sci. Technol.* **44**, 147–154 (2007). <https://doi.org/10.1080/18811248.2007.9711268>
121. L. Guo, C. Wan, H. Wu, Data assimilation for the burnup distribution applying the three-dimensional variational and artificial neural network algorithm. *Ann. Nucl. Energy* **179**, 109419 (2022). <https://doi.org/10.1016/j.anucene.2022.109419>
122. J. Lei, C. Yang, C. Ren et al., Development and validation of a deep learning-based model for predicting burnup nuclide density. *Int. J. Energy Res.* **46**, 21257–21265 (2022). <https://doi.org/10.1002/er.8338>
123. F. Courtin, B. Leniau, B. Mouginot et al., PWR mox fuel physics models for the dynamic fuel cycle simulation tool class. *Proc. Phys. Reactors (PHYSOR)* (2016). <https://hal.science/hal-04948200/>
124. S. Grape, E. Branger, Z. Elter et al., Determination of spent nuclear fuel parameters using modelled signatures from non-destructive assay and Random Forest regression. *Nucl. Instrum. Methods Phys. Res. A* **969**, 163979 (2020). <https://doi.org/10.1016/j.nima.2020.163979>
125. C.X. Soto, O. Dim, Y. Cui et al., A better method to calculate fuel burnup in pebble bed reactors using machine learning. *Nucl. Technol.* **209**, 1282–1294 (2023). <https://doi.org/10.1080/00295450.2023.2200573>
126. D. Salvato, K.M. Paaren, J.A. Hirschhorn et al., The effect of temperature and burnup on U-10Zr metallic fuel chemical interaction with HT-9: A SEM-EDS study. *J. Nucl. Mater.* **591**, 154928 (2024). <https://doi.org/10.1016/j.jnucmat.2024.154928>
127. M.R. Oktavian, J. Nistor, J.T. Gruenwald et al., Integrating core physics and machine learning for improved parameter prediction in boiling water reactor operations. *Sci. Rep.* **14**, 5835 (2024). <https://doi.org/10.1038/s41598-024-56388-5>
128. P. Wang, Z. Zhu, W. Liang et al., Hybrid mechanistic and neural network modeling of nuclear reactors. *Energy* **282**, 128931 (2023). <https://doi.org/10.1016/j.energy.2023.128931>
129. J.S. Palmer, C. Ritter, R.H. Stewart et al., Creation synthetic data to train a digital twin to predict reactor operations. Idaho National Laboratory (INL), Idaho Falls (2024)
130. S. Kollias, M. Yu, J. Wingate et al., Machine learning for analysis of real nuclear plant data in the frequency domain. *Ann. Nucl. Energy* **177**, 109293 (2022). <https://doi.org/10.1016/j.anucene.2022.109293>
131. H. Zhou, S. Cheng, R. Arcucci, Multi-fidelity physics constrained neural networks for dynamical systems. *Comput. Methods Appl. Mech. Eng.* **420**, 116758 (2024). <https://doi.org/10.1016/j.cma.2024.116758>
132. J.J.C. Dorville, Advancing nuclear reactor simulations using ray tracing, machine learning and kinematic models of energy deposition. PhD Dissertation, Colorado School of Mines (2024).
133. M.I. Radaideh, T. Kozlowski, Combining simulations and data with deep learning and uncertainty quantification for advanced energy modeling. *Int. J. Energy Res.* **43**, 7866–7890 (2019). <https://doi.org/10.1002/er.4698>
134. M.R. Oktavian, Development of a machine learning-assisted core simulation for boiling water reactor operations. PhD Dissertation, Purdue University (2023). <https://doi.org/10.25394/PGS.24302449.v1>
135. C. Wan, K. Lei, Y. Li, Optimization method of fuel-reloading pattern for PWR based on the improved convolutional neural network and genetic algorithm. *Ann. Nucl. Energy* **171**, 109028 (2022). <https://doi.org/10.1016/j.anucene.2022.109028>
136. A. Rasheed, O. San, T. Kvamsdal, Digital twin: values, challenges and enablers from a modeling perspective. *IEEE Access* **8**, 21980–22012 (2020). <https://doi.org/10.1109/ACCESS.2020.2970143>
137. K. Kobayashi, S.B. Alam, Deep neural operator-driven real-time inference to enable digital twin solutions for nuclear energy systems. *Sci. Rep.* **14**, 2101 (2024). <https://doi.org/10.1038/s41598-024-51984-x>
138. International Atomic Energy Agency, Safeguards criteria: special criteria for difficult-to-access fuel items. IAEA, Vienna (2015)
139. C. Wang, H. Wu, L. Cao, P. Yang, On-line reconstruction of in-core power distribution by harmonics expansion method. *Nucl. Eng. Des.* **241**, 3042–3050 (2011). <https://doi.org/10.1016/j.nucengdes.2011.05.013>
140. F. Caliva, F.S. De Ribeiro, A. Mylonakis et al., A deep learning approach to anomaly detection in nuclear reactors. *Proc. Int. Joint Conf. Neural Netw. (IJCNN)* Rio de Janeiro, Brazil, 2018, pp. 1–8 (2018). <https://doi.org/10.1109/IJCNN.2018.8489130>
141. H. Song, M. Song, X. Liu, Online autonomous calibration of digital twins using machine learning with application to nuclear power plants. *Appl. Energy* **326**, 119995 (2022). <https://doi.org/10.1016/j.apenergy.2022.119995>
142. R. Stewart, A. Shields, C. Pope et al., A digital twin of the AGN-201 reactor to simulate nuclear proliferation. *Proc. INMM/ESARDA Joint Annu. Meeting* (2023)
143. I. Pázsit, C. Demazière, Noise Techniques in Nuclear Systems, in *Handbook of Nuclear Engineering*, ed. by D.G. Cacuci (Springer, Boston, 2010)
144. P. Mena, R.A. Borrelli, L. Kerby, Detecting anomalies in simulated nuclear data using autoencoders. *Nucl. Technol.* **210**(1), 112–125 (2023). <https://doi.org/10.1080/00295450.2023.2214257>
145. M. Mendoza, P.V. Tsvetkov, An intelligent fault detection and diagnosis monitoring system for reactor operational resilience: fault diagnosis. *Prog. Nucl. Energy* **168**, 104989 (2024). <https://doi.org/10.1016/j.pnucene.2023.104989>
146. M. Mendoza, P.V. Tsvetkov, An intelligent fault detection and diagnosis monitoring system for reactor operational resilience: unknown fault detection. *Prog. Nucl. Energy* **171**, 105167 (2024). <https://doi.org/10.1016/j.pnucene.2024.105167>
147. A. Seki, M. Yoshikawa, R. Nishinomiya et al., Development of a surrogate system of a plant dynamics simulation model and an abnormal situation identification system for nuclear power plants using deep neural networks. *Nucl. Technol.* **210**(6), 1003–1014 (2024). <https://doi.org/10.1080/00295450.2023.2273566>
148. A. Kumar, P.V. Tsvetkov, A new approach to nuclear reactor design optimization using genetic algorithms and regression analysis. *Ann. Nucl. Energy* **85**, 27–35 (2015). <https://doi.org/10.1016/j.anucene.2015.04.028>
149. Y.M. Song, J. Mao, Z.H. Zhang et al., A novel multi-objective shielding optimization method: DNN-PCA-NSGA-II. *Ann. Nucl. Energy* **161**, 108461 (2021). <https://doi.org/10.1016/j.anucene.2021.108461>
150. X. Liu, Z. Wang, H. Ji et al., Application and comparison of several adaptive sampling algorithms in reducing order modeling. *Heliyon* **10**, e34928 (2024). <https://doi.org/10.1016/j.heliyon.2024.e34928>
151. K. Hadad, A. Piroozmand, Application of cellular neural network (CNN) method to the nuclear reactor dynamics equations. *Ann. Nucl. Energy* **34**, 406–416 (2007). <https://doi.org/10.1016/j.anucene.2007.02.001>

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.