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Review

Review on the Recent Progress in Nuclear Plant Dynamical Modeling and Control

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Abstract: Nuclear plant modeling and control is an important subject in nuclear power engineering, giving the dynamic model from process mechanics and/or operational data as well as guaranteeing satisfactory transient and steady-state operational performance by well-designed plant control laws. With the fast development of small modular reactors (SMRs) and in the context of massive integration of intermittent renewables, it is required to operate the nuclear plants more reliably, efficiently, flexibly and smartly, motivating the recent exciting progress in nuclear plant modeling and control. In this paper, the main progress during the last several years in dynamical modeling and control of nuclear plants is reviewed. The requirement of nuclear plant operation to the subject of modeling and control is first given. By categorizing the results to the aspects of mechanism-based, data-based and hybrid modeling methods, the advances in dynamical modeling are then given, where the modeling of SMR plants, learning-based modeling and state-observers are typical hot topics. In addition, from the directions of intelligent control, nonlinear control, online control optimization and multimodular coordinated control, the advanced results in nuclear plant control methods are introduced, where the hot topics include fuzzy logic inference, neural-network control, reinforcement learning, sliding mode, feedback linearization, passivation and decoupling. Based upon the review of recent progress, the future directions in nuclear plant modeling and control are finally given.

Keywords: nuclear plant; dynamical modeling; advanced control

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1. Introduction

System control, adjusting the state of actuators according to the system operational state measured by the sensors, is a key technique of all the industrial processes and equipment such as nuclear plants, fossil power plants, chemical plants, wind turbines, batteries, etc. For nuclear plants generating electricity and/or heat through nuclear fission reactions, system control keeps the deviations of process variables, with respect to their setpoints, satisfactorily bounded, while reducing the risk of reactor trip. Dynamical modeling is a precondition of system control design, describing plant dynamical characteristics by a set of differential, difference and algebraic equations obtained from the physical rules or operational data. Nuclear plant modeling and control is a hot spot in nuclear engineering since the 1950s, whose development is associated with the development of nuclear energy technology.

According to the number of nuclear reactors in a single unit, there are two types of nuclear plants, i.e., the single-modular nuclear plants and the multimodular nuclear plants. For the current large-scale commercial pressurized water reactors (PWRs) with rated thermal power over 3000 MW_t, the single-multimodular scheme is mostly adopted, and the corresponding schematic process diagram is shown in Figure 1. It can be seen from Figure 1 that a single large-scale PWR provides the heat for multiple U-tube steam generators

(UTSGs), the saturated steam flows generated by the UTSGs are combined together before entering into the turbine for electricity generation, and the condensed water is pressurized and heated up before being distributed to the UTSGs for the next cycle. For those small modular reactors (SMRs) with electric power output less than 300 MW_e, the multimodular scheme is usually adopted to build large-scale power plants. In a multimodular SMR plant, the motive steam provided by multiple nuclear steam supply (NSSS) modules are combined together to drive common thermal load equipment, such as steam turbines and cogeneration processes. Both the integral PWR (iPWR) and the modular high temperature gas-cooled reactor (mHGR) are typical SMRs. With comparison to the current commercial large-scale PWRs, the iPWR has a series of advanced features such as the integral primary circuit, natural-circulation and self-pressurization, as well as passive decay heat removal. The mHTGR uses helium as coolant and graphite as both the moderator and structural material. The fuel element of mHTGR is made by embedding thousands of TRISO coated particles into the prismatic or spherical graphite matrix, and the silicon carbide (SiC) layer of TRISO particle is able to prevent the leakage of fission products under 1620 °C. By limiting its power density no higher than 3 MW/m^3, about one-thirtieth of the power density of those 3000 MW_t-level commercial PWRs, the mHTGR can be endowed with the attractive inherent safety. Based on the multimodular scheme, the inherent safety can be applied to large-scale power plants with any desired power ratings. The schematic process diagram of a typical multimodular mHTGR power plant is shown in Figure 2. Every NSSS module is mainly composed of an mHTGR, a helical-coil once-through steam generator (OTSG) and a primary helium blower. The primary helium heats up the secondary feedwater flow of OTSG to be superheated by steam, the superheated steam flows from multiple modules are combined and guided to the turbine and the condensed water is pressurized and heated up before being distributed to the modules.

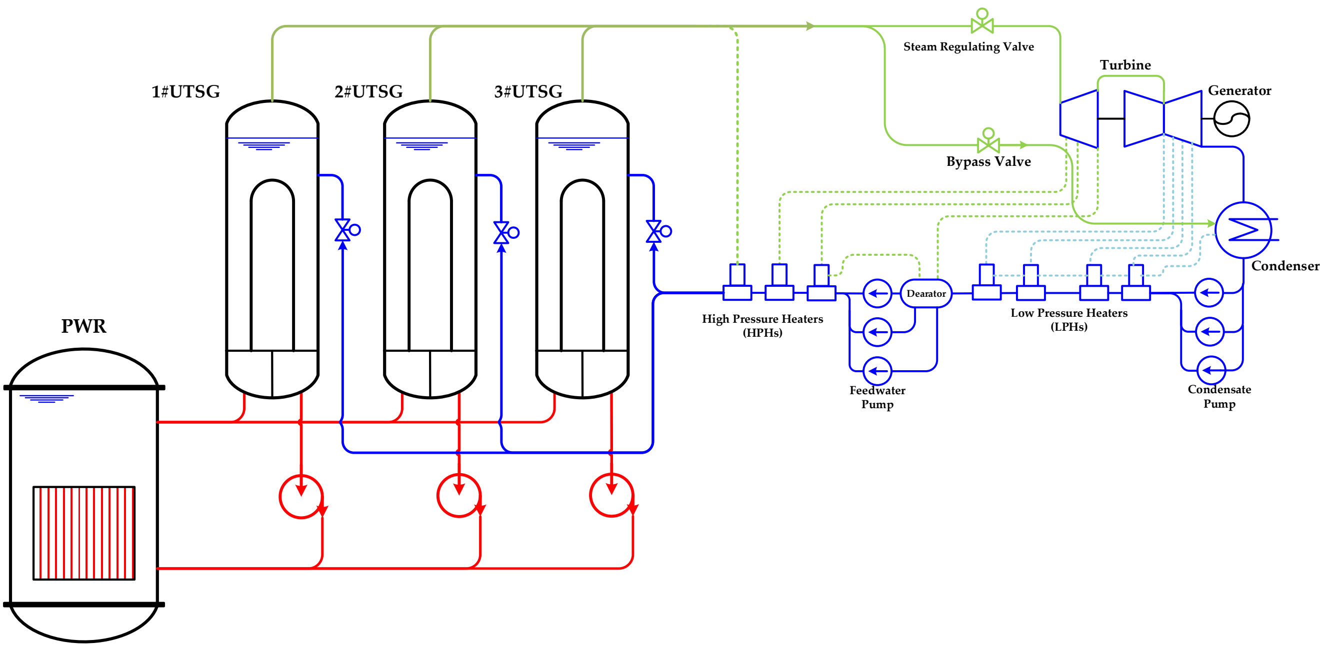

Figure 1. Schematic diagram of a single-modular PWR plant, UTSG: U-tube steam generator. The red lines denote the primary coolant, the blue lines denote the secondary coolant in liquid state, and the green lines denotes the secondary coolant in steam state.

Nuclear reactor power-level control is the most important topic in the control of single-modular nuclear plants, and the majority of archival research results are related to the power level control of nuclear reactors. The basic principle of reactor power level control is to generate the driving signals of actuators from the measurements of concerned process variables, including neutron flux and primary coolant temperature, so as to guarantee satisfactory closed-loop stability. If the control rods are chosen as the actuators, then the schematic diagram of power level control is shown in Figure 3, from which it can be seen that both the neutron flux and the primary coolant temperature are controlled. More specifically, if the average coolant temperature is required to be controlled, then the schematic diagram of power level control is given by Figure 3a. If the outlet coolant temperature control is required, then the schematic diagram is shown in Figure 3b. Further from Figure 3, the input signals of power level controller are the errors of neutron flux and average (or outlet) primary coolant temperature, being defined by the deviations of the measurements of process variables from their setpoints. The output of controller is the control rod speed signal driving the control rods for proper reactivity injection or withdrawal. The measurement signal of neutron flux shown in Figure 3 is provided by the sensors, such as ion-chamber detectors, and the measurement of average coolant temperature is the algebraic mean of the measurements of coolant temperatures at reactor inlet and outlet. Actually, no matter which type a nuclear fission reactor is, it is always a complex nonlinear dynamical system with uncertainties and disturbances. With the recent vast integration of wind turbines and solar PV units, it is urgently required to balance the intermittent renewables with nuclear power, relying heavily on reactor power level control. For guaranteeing satisfactory performance in power level maintenance, maneuvering and load-following, many advanced power level control methods, e.g., intelligent and nonlinear control methods, have been proposed recently.

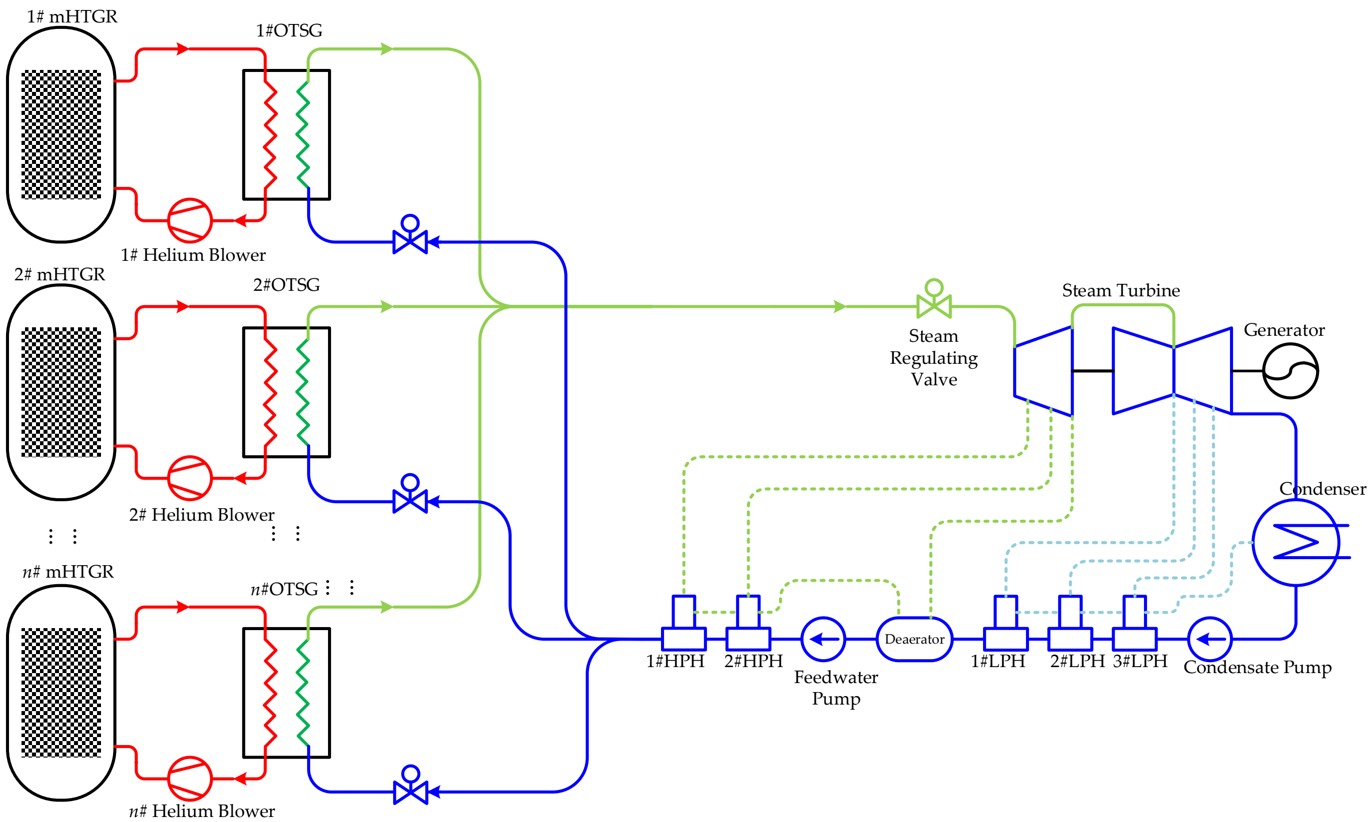

Figure 2. Schematic diagram of a mutimodular mHTGR plant, OTSG: once-through steam generator, HPH: high pressure heater, LPH: low pressure heater. The red lines denote the primary coolant, the blue lines denote the secondary coolant in liquid state, and the green lines denotes the secondary coolant in steam state.

For multimodular nuclear plants, although the reactor power level control is still an important topic, the coordinated control of multiple SMR-based NSSS modules is the basic and most crucial control problem. Actually, from the schematic process diagram shown in Figure 2, the variation in the feedwater-regulating valve opening of an arbitrary

NSSS module changes the feedwater flowrates of all the modules, which further leads to variations in motive steam temperature, primary helium temperature and neutron flux of all the modules. In addition, the variation in the motive steam temperature of a single module causes the variations in feedwater temperature of all the modules through the common feedwater heaters. Furthermore, the variation in the opening of the steam regulating valve at the inlet of steam turbine changes the main steam pressure, which in turn induces the variations of secondary and primary process variables of every module. Hence, multiple NSSS modules are tightly coupled by the common conventional island, and it is necessary to develop the multimodular coordinated control theory for realizing the decoupling control of multiple modules. Based on the multimodular scheme, the inherent safety feature of a single SMR can be applied to those large-scale plants with any desirable power ratings, showing that the multimodular coordinated control plays a key role in the development of SMR technology. Very recently, some promising results in multimodular coordinated control have been proposed and applied to the high temperature gas-cooled reactor pebble-bed module (HTR-PM) demonstration plant in China.

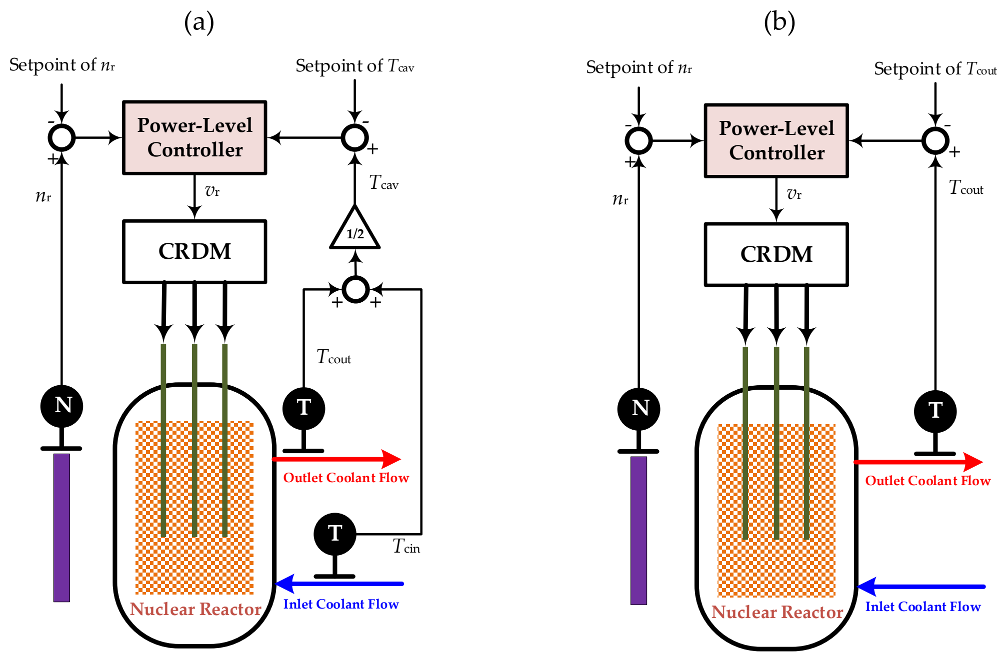

Figure 3. Schematic principle of nuclear reactor power level control, (**a**) power level control scheme for neutron flux and average primary coolant temperature, (**b**) power level control scheme for neutron flux and outlet primary coolant temperature, n_r: normalized neutron flux, T_{cout}: primary coolant temperature at the reactor outlet, T_{cin}: primary coolant temperature at the reactor inlet, T_{cav}: average primary coolant temperature, v_r: control rod speed signal, CRDM: control rod driving mechanism.

Due to the recent progress in nuclear energy systems, especially the SMRs, and motivated by the requirement of balancing renewables with nuclear, there have been a series of interesting and promising results in the modeling and control of nuclear plants. The main contribution of this study is reviewing the very recent progress in nuclear plant dynamical modeling and control and giving some suggestions on future research directions. First, the recently published results are categorized to the aspect of dynamical modeling and that of plant control. Further, the results in dynamical modeling are summarized to the aspects of mechanism-based modeling, data-based modeling and hybrid modeling. In addition, the results in plant control are categorized to the aspects of intelligent control, nonlinear control, online control optimization and multimodular coordinated control. Finally, the future developing trend of nuclear plant modeling and control is given, pointing out that the combination of nonlinear control, artificial intelligence and online optimization is meaningful in enhancing nuclear plant operational performance.

2. Dynamical Modeling

Dynamical modeling is the precondition for the design and verification of controllers. Usually, the models can be obtained based upon the process mechanism or directly from the operation data. The mechanism-based models take the form of ordinary differential equations (ODE), partial differential equations (PDE), transfer functions, etc., being given by the conservation laws of mass, momentum and energy, while those data-based models are mostly given by neural networks trained offline or online by the samples from the recorded operational data sets.

2.1. Mechanism-Based Modeling

Currently, the dynamical modeling of SMRs based on the conservation laws of mass, momentum and energy is a hot topic. In [1], Poudel, Joshi and Gokaraju proposed the dynamical model of an integral pressurized water reactor (iPWR)-type SMR for assessing its influence to power system operation. This iPWR model mimics the heat generation and transfer processes with the inclusion of the reactor core, naturally circulated primary loop and steam generator. In [2], Poul and Gokaraju coupled the SMR with those renewables for supplying electricity and district heating, and further proposed a simulation model of this hybrid energy system. The corresponding simulation results showed that cogeneration as well as the storage of heat and electricity have potential benefits for the flexible operation of SMRs. In [3], a lumped-parameter dynamical model of the sea water desalination plant based on the nuclear heating reactor (NHR) and the multi-effect-desalination and thermal-vapor-compression (MED-TVC) process was proposed for control design and verification. In addition to SMR modeling, the dynamical modeling of multimodular nuclear plants is also a hot topic. In [4], a lumped-parameter model was proposed for the six-modular mHTGR plant HTR-PM600, which is composed of the models of NSSS modules, steam-turbine, condenser, deaerator, feedwater heaters, feedwater pumps, regulating valves, secondary fluid flow network, synchronous generator and a multimachine power system. In [5], a dynamical model of the hydrogen production process constituted by the copper-chlorine (Cu-Cl) cycle and high temperature electrolysis (HTE) was given. By combining with the power plant model given in [4], the dynamical model of an mHTGR-based nuclear power–hydrogen cogeneration plant was also proposed in [5].

Although the majority of mechanism-based dynamical models is described by a set of ODEs or PDEs, transfer functions can be also applied for modeling. In [6], the transfer functions were adopted to describe the decaying dynamics of fission products, and a Bode-step controller was then designed to compensate for the phase lag. Moreover, since the mechanism-based dynamical models can provide enough details in system dynamics, they are suitable for building simulators for the verification of operation and control strategies. In [7], a hardware-in-the-loop (HIL) emulation testbed was developed for the control system verification of a nuclear submarine.

2.2. Data-Based Modeling

With comparison to those mechanism-based models being mainly applied for control design and verification, data-based models are usually adopted for condition monitoring and prediction. Data-based dynamical modeling is a black-box method, determining the parameters of the model with a given topology purely from operational data.

Recent progress in data-based modeling focuses on using neural networks and deep learning to learn the concerned sophisticated reactor dynamics. In [8], a neural network was combined with INCOPW process code to build the core monitoring system for Chashma Nuclear Power Plant Unit 1. Aiming for a rapid emergency response, the multilayer perception (MLP) was trained by the backpropagation (BP) algorithm to learn the interaction mechanism between the reactor core and the coolant system in the primary and secondary circuits [9]. In [10], a recurrent neural network (RNN) was applied to learn a single-input-single-output (SISO) channel of PWR dynamics, where the architecture of RNN was given by the evolutionary algorithms and the gradient descent algorithms.

In [11], the principle component analysis (PCA) was applied to reduce the dimension of data space, and a deep neural network (DNN) was trained by the reduced-order samples to learn the time-dependent reactor transients.

Data-based modeling has a great potential in condition prediction, and several interesting results have been given very recently. In [12], a deep learning program was developed to predict reactor thermal-hydraulic parameters, which was applied to the KLT-40S reactor. This program mainly consisted of the modules of neural network, activation function, error function, initialization and optimization. For strictly controlling the radiation dose in normal conditions, a dynamic Bayesian network (DBN) was applied to predict the radioisotope concentrations [13]. The results in five different nuclear power plants (NPPs) show that the accuracy and reliability of this DBN-based method is remarkable, enabling possible operation improvements. By combining the ensemble empirical mode decomposition (EEMD) and long short term memory (LSTM) neural network, a multi-step signal prediction method was proposed for strengthening the maintenance planning and avoiding unexpected shutdowns [14]. The EEMD was responsible for decomposing the time series into a set of intrinsic mode function components, and the LSTM network performed the prediction based on the decomposed components.

2.3. Hybrid Modeling

From the discussions in Sections 2.1 and 2.2, mechanism-based modeling is purely based on the neutron kinetics and thermal-hydraulics of NPP, while the data-based modeling is purely based on the training samples generated from operational data. The performance degradation of mechanism-based models is mainly induced by the unmodeled dynamics and the parameter uncertainty of modeled dynamics, while the performance degradation of data-based models is mainly given by the lack of training samples. There is a strong complementarity between the mechanism-based modeling and the data-based modeling. The process mechanism can improve the certainty of dynamical models, and can mitigate the training load to a large extent. The operation data can be utilized to enhance the adaptation of models, and can further suppress the modeling uncertainties. Due to the strong complementarity between the process mechanism and operational data, it is natural to develop the hybrid dynamical modeling methods, which is the hot spot in the area of nuclear plant modeling.

The state-observers are typical hybrid models, providing the estimation of internal and unmeasurable process variables by combining a mechanism-based process dynamical model with measurement data. Very recently, some promising results have been given to the state-observer design of nuclear reactors. In [15], a Rao–Blackwellised unscented Kalman filter (RBUKF) was proposed for the adaptive state-observation of nuclear reactors, being able to give the estimation of reactivity from the measurement signal from neutron detectors. The RBUKF was superior to the classical Kalman filter and unscented Kalman filter in its robustness against noises. To handle the limitation of the Kalman filter in the lack of adding constraints on state-variables, a constrained estimator was proposed based on the recursive dynamic data reconciliation, which was able to provide the estimation of reactivity and precursor concentrations [16]. In addition to the Kalman filter based state-observation methods [15,16], some nonlinear state-observers have been developed very recently, such as the sliding mode observer (SMO), dissipation-based high gain filter (DHGF) and extended state-observer (ESO). In [17], a high order sliding mode observer (HOSMO) was proposed for estimating the poisoning reactivity of PWRs, where the inherent chattering effect of classical SMO can be effectively avoided by adopting the high-order sliding mode. Based on the DHGF initially presented in [18], the adaptive DHGF for nuclear reactors was proposed in [19], needing only the measurements of neutron flux and coolant temperature at reactor inlet, and being able to provide the estimation for the concentrations of delayed neutron precursors, xenon-135 and iodine-135, the average temperatures of fuel elements and primary coolant as well as the reactivity disturbance. By regarding the disturbances in the measurement channels as extended state variables, the ESO can be used for disturbance observation, which is crucial in monitoring the reactor's condition. However, since the classical ESO is given for the dynamic systems represented in the Brunovsky normal form, it is necessary to provide ESO for passive process systems such as a nuclear fission reactor. In [20], by viewing the total reactivity as an extended state-variable, the ESO of neutron kinetics was proposed, which was prior to the classical inverse point kinetics (IPK) method in providing a reactivity estimation in subcritical conditions. In [21], an ESO of nonlinear passive systems was proposed to estimate the total disturbances and their first and second order time-derivatives in measurement channels, which was further applied for the online assessment of NPP operational reliability. With comparison to the ESOs in [20,21] that the measurement errors are fed to back for estimating internal and extended state variables, the proportional-integral ESO (PI-ESO) presented in [22] gave asymptotic estimations based on not only the measurement errors but also their integrations over time. To further improve the performance of ESO with historical measurements, the neural network ESO (NN-ESO) of passive process systems was given by combining the MLP and ESO [23], where the MLP was trained online by the measurements for asymptotic convergence.

As the dynamical models are necessary for the design of state-observers such as SMO, DHGF and ESO, the values of model parameters influence the observation performance to a large extent, leading to the importance of parameter estimation. In [24], nonlinear least square (LS) method was applied to estimate both the physical and thermal-hydraulic parameters of high temperature gas cooled test reactor HTTR with a rated thermal power of 30 MW_t, where the data were given by tests of withdrawing the control rods at the power levels of 9, 15 and 18 MW_t. In addition to the internal and extended states, the derivatives of measurement signals over time can also reflect the operating condition of industrial processes including nuclear reactors. In [25], a finite-time convergent differentiator was proposed for the estimations of first and high-order time-derivatives, which was then applied for assessing the growth rate of neutron flux.

The hybrid models, such as the state-observers, are widely applied to fault detection and diagnosis, serving as analytic redundancies. In [26], an observer-based fault detection algorithm was proposed for the water-level sensor of UTSGs. If the consistency between the measured and observed values was violated, then the sensor fault would be detected. In [27], a fault detection and isolation (FDI) method given by multiscale PCA was given for the advanced heavy water reactors, where the measurement signals were decomposed into several time-scales by applying wavelet transformation, and then the PCA was used to provide analytical redundancy for FDI for every frequency domain. In [28], a fault diagnosis method was given for small PWRs, and the analytical redundancy was provided by the LSTM network, being trained for giving the long-term dependency of the concerned faults on the responses of process variables.

3. Plant Control Methods

The task of modeling is to describe the dynamical behavior of NPPs by the means of differential equations, discrete-time equations, artificial neural networks, state-observers, etc., while that of control is to intervene in the NPP dynamics for better operational performance through properly driving the movement of actuators based on feeding back the measurements and feeding forward the setpoint. As NPPs are sophisticated human-cyber-physical systems (HCPS), it is necessary to mitigate the working load of operators by improving the intelligence level of the control system, helping to transform the central task of operators from the manual control of processes to the handling of complex and uncertain conditions [29]. Many interesting results about the intelligent control method of NPPs have been proposed very recently. Since the nonlinearity of NPP dynamics cannot be simply omitted in the condition of load-following, it is necessary develop nonlinear control methods able to guarantee global or wide-range closed-loop stability. For better steady and transient responses of key process variables, the control optimization methods, such as the model predictive control (MPC), have been deeply investigated. As large-scale NPPs can be built by combing the superheated steam flows from multiple SMR-based NSSS modules, the multimodular coordinated control has been a key technology of SMR, gaining more and more attention very recently. In the following parts of this section, the current status about the development of NPP control is given in detail from the aspects of intelligent control, nonlinear control, online control optimization as well as multimodular coordinated control.

3.1. Intelligent Control

The studies on the intelligent control of NPPs focus on the combination of classical proportional-integral-differential (PID) control and linear state-feedback control with soft computing (SC) techniques for possible performance improvement. SC refers to a group of computation techniques independent of mathematical models, such as artificial neural network (ANN), fuzzy sets and evolutionary algorithms [30].

The practical nuclear reactor control is mostly realized by the classical proportional-integral-differential (PID) feedback law. However, due to strong nonlinearity of nuclear reactor dynamics, the feedback gains of a PID controller giving satisfactory regulation performance usually vary with power levels. How to combine the PID gains tuned in different power levels? A practical scheme is to endow the set of PID gains corresponding to a given power level with membership functions, and then determine the PID gains at any other power levels using fuzzy logic inference (FLI). In [31], this fuzzy-logic-control design method was applied to design the fuzzy PID control for maintaining the secondary average coolant temperature of an accelerator driven system. In [32], the FLI was applied to design the fuzzy PID control for space nuclear reactor TOPAZ-II. In [33,34], by applying FLI, the fuzzy PID controllers of core power and core outlet temperature were designed for the molten salt reactor (MSR). Here, the MSR refers to the nuclear fission reactor using molten fluoride as the primary coolant while operating at a low pressure with epithermal or fast neutron spectrums. The central MSR concept is the fuel salts given by dissolving the fuel in the primary fluoride. The fluoride is mostly lithium-beryllium fluoride or lithium fluoride, remaining liquid from 500 to 1400 °C in atmospheric pressure.

Actually, the FLI can also be applied for the interpolation from any other types of banks of controllers, models and even setpoints. In [35], a wide-range fuzzy fractional order PID controller for the average thermal power of PWR was synthesized from a set of local fractional order controllers, where the PID gained of local controllers as well as optimizing the membership functions for better control performance. In [36], a wide-range dynamical model of PWR core was given by the fuzzy logic inference of the local transfer functions at five different power levels, and a gain-scheduling PID law was applied for reactor power level control. In [37], a fuzzy input-output reactor dynamic model was obtained from the fuzzy logic inference (FLI) of a set of linear parameter varying (LPV) models describing the local dynamics, and then a wide-range robust control law was given by the fuzzy interpolation of several local H_∞ controllers. Similar to the FLC design in [37], a LPV model set of a VVER-1000 reactor core was given by the identification of a two-point kinetic model with consideration of neutron diffusion, thermal-hydraulics and poison concentration at several power levels, and then the controllers for both reactor power level and power distribution were obtained by the fuzzy interpolation of local controllers associated with the LPV models [38]. In [39], by adopting a nonlinear four-point kinetic model of a VVER-1000 reactor, the adaptive power tracking control was designed by applying the fuzzy inference strategy similar to that in [38]. By identifying the model set at various operating power levels from the input-output data of a simulator, a robust fuzzy gain-scheduling control was designed for lead cooled fast reactors (LFR) based upon fuzzy inference [40]. In [41], the fuzzy inference was applied to adjust the gains of a proportional-integral (PI) outlet pressure controller for the OTSG of an SMR according to the magnitudes of control errors. In [42], the pressure setpoint of a pressurizer was modified by FLI for stabilizing primary pressure during some severe transients.

With comparison to fuzzy sets, neural networks can be applied not only for the interpolation of setpoints, gains, models and controllers but also for the approximation of nonlinear dynamics or even optimal control laws. The similarity between ANNs and fuzzy systems is strong, e.g., the structure of the radial basis function (RBF) neural network is nearly the same as a fuzzy inference system. In [43], the PID gains of a PWR power level controller were adjusted by an RBF network whose weights were optimized online by a particle swarm optimization (PSO) algorithm. In [44], the RBF network was applied for the estimation of the uncertainty given by device malfunction, unmodeled dynamics and exterior disturbances, and a compensation control action for the tolerance against faults. In addition to the RBF network, the multi-layer perception (MLP) is another commonly utilized neural network, where the former one is a linearly parameterized network while the latter one is a nonlinear parameterized network. Actually, the MLP can be adopted to approximate sophisticated unknown dynamics. To apply the feedback linearization control method for enhancing load-following performance, the MLP was applied to approximate the uncertain internal dynamics online, and an adaptative control mechanism was further given for power tracking [45]. In [46], the MLP was coupled with a fuzzy set system for the simultaneous control of power level and power distribution, where the scaling factor of the input fuzzy universe was adjusted online by the MLP. Moreover, the ANNs, such as the RBF, MLP, RNN and LSTM networks, are the basic tools for realizing reinforcement learning control (RLC) and deep learning (DL) based operations. In [47], the integral reinforcement learning control (iRLC) method was proposed for optimized load-following control under the framework of adaptive dynamic programming (ADP), where the neural networks were utilized to approximate both the performance index and control law solving the Hamilton–Jacobi–Bellman (HJB) equation. In [48], the LSTM network and its associated DL algorithm was applied for realizing autonomous power-increase operations, which could lower the working load of operators. In [49], an MLP-based RLC method was proposed for a nonlinear dissipative system, composed of an MLP-based state-observer and an approximate optimal controller. The approximate optimal controller was designed by solving an algebraic Riccati equation with its parameters given by the MLP-based observer. This MLP-based RLC has been applied to the optimization of reactor thermal power response.

From the above introduction about the current progress in intelligent control of NPPs, it can be seen that the intelligence from fuzzy sets and neural networks focuses on addressing nonlinearity and providing adaptation. If there is a bank of local PID or state-feedback control laws designed at a set of power levels, then the global control for a wide power range can be obtained by the FLI on the bank of local controllers. With comparison to FLI, neural networks are more suitable to be used for the estimation of uncertainty, and the compensating control action can then be given based on this estimation. Due to its features of being model-free and having strong adaptation, the RLC is gaining more and more attention. Actually, neural networks play a central role in the RLC in learning both the performance index and control action online from the interaction with the environment.

3.2. Nonlinear Control

With comparison to local controllers being suitable for power level maintenance, the global controllers can provide closed-loop stability in a wide power range, which is positive for load-following. Although the global control can be obtained using the fuzzy inference from a set of local controllers designed by classical control theory or linear system theory, the global control can also be determined with nonlinear control theory. For example, with comparison to classical linear PI control, the nonlinear PI output power control given in [50] can provide closed-loop stability in a wider power range, where the proportional and integral gains are nonlinear functions of power level. Actually, nonlinear control of nuclear reactors has been a hot spot since the middle of 1990s, and some interesting results have been given very recently. The sliding model control (SMC), passivity-based control (PBC) and feedback linearization control (FLC) are three main nonlinear control methods for nuclear reactors.

Due to the capability of handling nonlinearity and uncertainty, SMC methods of nuclear reactors are studied, and some promising results are given. In [51], an SMC using constant axial offset strategy was proposed for bounding the xenon oscillation, which can be applied for wide-range load-following. In [52], a state-feedback SMC was proposed for load-following control of reactor power, where the estimation of concentrations of delayed neutron precursors was provided by a SMO. Based on the Lyapunov direct method, it was shown that this SMC–SMO coupled dynamic output feedback reactor power control can provide asymptotic closed-loop stability. In [53], an adaptive SMC for attenuating xenon oscillation was designed based on the two-point kinetics reactor model, where an adaptive observer was given for estimating the unmeasurable states and internal process parameters. To attenuate the inherent chattering effect of classical SMC, high order SMC was developed for enhancing closed-loop robustness. In [54], a robust optimal integral SMC (iSMC) was proposed for the load-following control of PWRs, where the performance was optimized by the linear quadratic Gaussian/loop transfer recovery (LQG/LTR) strategy, while the robustness was provided by the iSMC. In [55], a generalized ESO was given for the observation of system states and mismatched uncertainties, and an iSMC was proposed to eliminate these uncertainties. In [56], a second-order SMC was given for PWR power level control, where a twisting algorithm was adopted for scheduling the control gains adaptively according to power requirement. In addition, to avoid chattering based on high-order sliding mode surface, a boundary layer technique based on smooth switching function was used to suppress the chattering phenomenon [57]. Moreover, SMC can also be utilized to enhance the performance of implemented control systems. In [58], the super-twisting SMC (STSMC) was applied to strengthen the robustness of PID control laws by estimating and attenuating the internal and external disturbances. In [59], an iSMC was designed to associate with a classical H∞ robust controller for better performance, where the iSMC was responsible for disturbance attenuation.

Feedback linearization uses state-feedback transformation to convert an n^{th}-order nonlinear dynamic system to the n^{th}-order integrator chain, i.e., the Brunovsky normal form, and then the controller can be designed based on linear control methods such as the pole placement. The state-feedback transformation is essentially a state-feedback control designed based on the accurate model of the concerned systems. Since the dynamical model of mechanical machines as well as electrical motors and generators are relatively easier obtain than the industrial processes, feedback linearization control (FLC) is usually applied in the motion control area. Recently, FLC has begun to be used in the control of neutron flux and poison concentrations. In [60], the FLC was applied to the neutron flux control of molten salt reactors (MSR) for desirable tracking performance, and the closed-loop stability was guaranteed by the state-feedback transformation and a simple proportional control. Since the accurate dynamic model was necessary to obtain the state-feedback transformation, how to address the uncertainty and disturbance was the central problem to be solved in the design of FLC. In [61], an observer was proposed for the estimation of both unmeasurable signals and modeling errors, and an approximation version of exact FLC was given based on the estimations. Similarly, an SMO was used to estimate the unmeasurable process variables, including concentrations of xenon-135 and delayed neutron precursors, and the FLC was then given based upon these estimations for stabilizing the spatial power distribution of a VVER-1000 reactor [62]. Further, another virtue of FLC is that it is an effective decoupling control design method, which is meaningful for those sophisticated industrial process systems. In [63], the pressure and water-level decoupling control for the pressurizers in PWR plants was proposed based upon the basic idea of FLC.

In addition to the SMC and FLC, the passivity-based control (PBC) is another effective nonlinear control method of nuclear plants. The PBC was developed based on the fact that nuclear reactors are passive nonlinear systems [64]. With comparison to the SMC and FLC usually leading to complex algorithms, the PBC can guarantee closed-loop stability of nuclear plants only by the use of simple control laws [65]. Recently, there has been some promising progress in the PBC of nuclear reactors or plants. In [66], the port-Hamiltonian form (PHF) of general nuclear reactor dynamics was first proposed, giving the manner of strengthening the passivity by feedback. In [67], a simple PBC was proposed for nuclear power level control, where the control action was determined by the control errors as well as their time-derivatives and weighting integrations. Based on the idea of PBC, a cascaded power level control of high temperature gas-cooled reactors (HTGR) was given in [68], which regulates the reactor power only by adjusting the primary helium flowrate. As the heat exchanger networks (HENs) commonly exist in industrial processes such as nuclear plants and chemical plants, the passivity of HEN dynamics was shown, and then a PBC was given for HEN to control the coolant temperature at the primary and secondary outlets [69]. To design the PBC of nonlinear disturbed systems, it is necessary to develop proper disturbance observation methods. In [70], the automatic generation control of a multimodular HTGR plant was transferred to the problem of disturbance attenuation of nonlinear systems. Then, an ESO was proposed for disturbance observation, and a PBC was given for the stabilization of grid frequency. Similarly, the cogeneration control problem of nuclear plants can be solved by the passivity-based disturbance attenuator given by the ESO for observing disturbances and the PBC for stabilizing main steam pressure [71]. By properly constructing the storage function, the PBC can also be applied for the stabilization of nuclear reactor power distribution [72].

Nonlinear control methods deal with the nonlinear dynamics of nuclear reactors or nuclear plants directly, giving global bounded or asymptotic closed-loop stability. Nonlinear control is meaningful for the load-following of nuclear plants, and the SMC, FLC and PBC are the current three main nonlinear control methods. The SMC drives the system dynamics to the designed sliding mode surface using feedback control, providing satisfactory robustness to disturbance. The inherent chattering phenomenon of SMC can be avoided by the techniques of either high-order sliding mode or boundary-layer. Based on the accurate model, FLC converts the system dynamics to the Brunovsky normal form by applying state-feedback transformation. For systems with uncertainty, approximate FLC can be given by estimating and attenuating internal and external disturbances. The PBC gives simple control laws by fully using the inherent passivity of the concerned system, being meaningful in engineering deployment. The key issue of PBC design is to find the storage function describing the passivity of the concerned system quantitively. Based upon the interconnection with disturbance observers given by the techniques of SMO, ESO, etc., the PBC can be utilized for disturbance attenuation, being attractive in both the simplicity of control algorithms and the feasibility of engineering deployment.

3.3. Online Control Optimization

Although closed-loop stability is the basic requirement of control design, some additional performance indices should be guaranteed for operation optimization, which leads to the necessity of developing optimized control methods. Currently, the model predictive control (MPC) is the most deeply studied and widely adopted online control optimization method. The MPC solves an optimization problem for a finite future at the current time, and implements the first optimal control input as the current control input.

The MPC was introduced to the field of nuclear plant control in the 2000s [73]. Very recently, there have been some interesting results in the MPC of nuclear plants. In [74], a nonlinear MPC (nMPC) was proposed to control the axial offset of reactor core power with respect to hard actuator constraints, and a simplified multi-point model was adopted for prediction. It can be seen that the multi-point model is a mechanism-based prediction model. In [75], an explicit MPC (eMPC) was designed for directly controlling the core power of MSR, where the performance index was the integration of the square of core power during a given period of prediction. Actually, the model can also be given by the operational data. In [76], the prediction model was given by an input-output data set, and the control parameters were recursively updated by the arrival of new data samples. The input-output data can be represented by the dynamical matrix, whose columns are the step responses of controlled variables with respect to a given manipulated variable. The dynamical matrix can be measured practically, and can also be adopted as the prediction model. Usually, the MPC using dynamic matrices as the prediction model is called dynamic matrix control (DMC). In [77,78], the DMC was adopted to optimize the transient responses of the thermal power of an mHTGR-based NSSS module, where no analytical process model was needed. Moreover, the prediction model can also be given by neural networks. In [79], a neural network MPC was given for the power level control of small PWRs, where the neural network was trained by multiple linear reactor models at a given set of power levels. In [80], the MLP-based MPC was proposed for the optimization of NSSS thermal power response, where the MLP was purely trained online with operational data by the algorithm being able to guarantee closed-loop stability.

In practical engineering, the MPC-based optimized control strategies usually operate in cooperation with local PID controllers. Actually, MPC modifies the setpoints of local PID controllers so as to optimize the operational performance. Since it is difficult to obtain the accurate dynamic model of the system coupled by the control object and the local controllers, the data-based MPC, such as the DMC and the neural network MPC, are more feasible to be deployed in the engineering.

3.4. Multimodular Coordinated Control

Multimodular nuclear plants refer to those SMR-based nuclear plants where the motive steam generated by the multiple SMR-based NSSS modules are combined together to drive a common or a common set of load equipment such as a steam turbine or a seawater desalination process. The multimodular coordinated control (MCC) method gives the control design methods of multimodular nuclear plants, which is currently a hot spot in the field of nuclear plant control and operation. It can be seen that in a multimodular nuclear plant, multiple NSSS modules are coupled tightly by the common load equipment, and the variation in the operational state of one NSSS module can influence the operation state of all the other modules. Although the control of a single NSSS module is still a concerned problem [81,82], the central issue in the MCC is the modeling of coupling effect amongst multiple modules and the related decoupling control for guaranteeing the stability of multiple modules.

The MCC is one of the key techniques in the development of multi-SMR-based nuclear plants; the MCC method of a multimodular plant with every NSSS module generating superheated steam is systematically developed in [83,84]. The coupling effect of multiple NSSS modules is modeled as a fluid flow network (FFN). Based on the branch fluid dynamics, as well as the algebraic constraints given by the mass conservation at a node and the zero-pressure-drop along a loop, the dynamics of a FFN can be modeled as a nonlinear differential algebraic system (DAS). The decoupling control of multiple NSSS modules can be realized by the pressure control of tree branches and the flowrate control of link branches. The pressure and flowrate control of FFN is further converted to the stabilization of the DAS near a given setpoint. The MCC designs for the independent and main-pipe feedwater schemes are proposed in [83] and [84], respectively. Moreover, the MCC method has been applied to design the coordinated control system (CCS) of the HTR-PM plant, the world's first commercial multimodular HTGR plant. The HTR-PM reached its initial full power with stable operation under the mode of "two reactors with one machine" on 9 December 2022 [85]. The main steam pressure of the HTR-PM plant is controlled automatically by the CCS during power increasing and maintenance.

After the pioneering work in [83,84], the decoupling control designs of multiple reactors and multiple steam turbines were recently given in [86,87], where the transfer function was first obtained from a simulation model and the decoupling control was then designed based on classical control theory. In addition, although the MCC method not only realizes decoupling control but also guarantees asymptotic closed-loop stability, the transient responses of some crucial process variables need further optimization. In [88], based on the DMC method, the thermal power responses of all the NSSS modules were optimized simultaneously by adjusting the setpoint of reactor neutron flux. Further, the coordinated control between the plant and electrical grid is also an important issue, where the mostly concerned control problem is how to stabilize the grid frequency by multimodular nuclear plants. In [70], the automatic generation control (AGC) method of multimodular NPPs was proposed, where several NSSS modules operated in load-following mode while the others operated in the base-load mode. The power level setpoints of the load-following modules were adjusted to stabilize the grid frequency. In [71], the AGC method of mutimodular nuclear cogeneration plants (NCPs) was proposed, where all the modules operated in the base-load mode, and the main steam pressure was stabilized by properly distributing the motive steam between the turbine and the cogeneration processes for producing hydrogen, potable water, etc.

4. Concluding Remarks and Future Directions

In the preceding sections, the recent progress of dynamical modeling and control design was reviewed, and the novelty and contribution of these archival works was summarized. The mind map briefly summarizing the main content of the technical review given in Sections 2 and 3 is illustrated in Figure 4, where the directions in dynamical modeling and control as well as some key words showing the main progress corresponding to every direction are all given. It can be further seen that the recent progresses focus on combining the knowledge of process mechanism and operation data for better modeling and control performance.

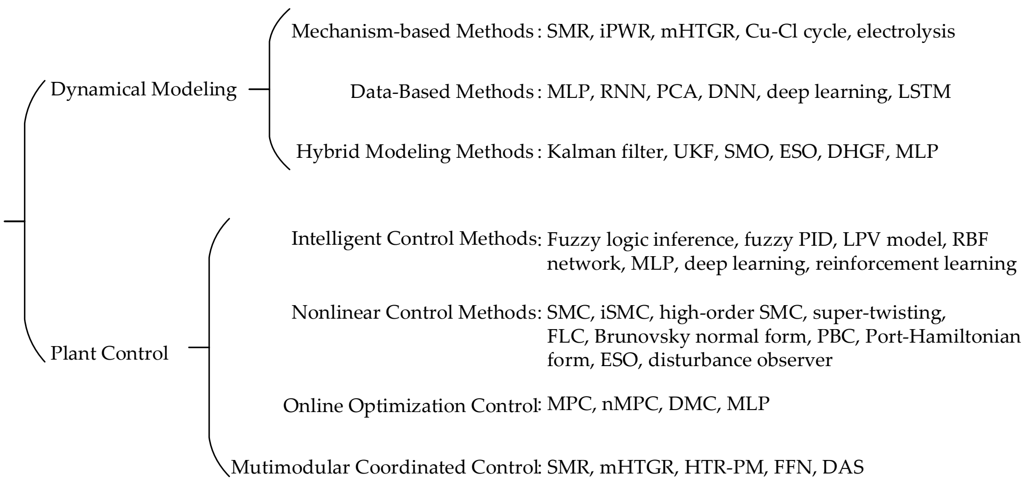

Figure 4. Mind map of technical review in Sections 2 and 3.

In the future, the central task of nuclear plant modeling and control is to improve the operational reliability, efficiency, flexibility and intelligence while enhancing the friendliness of nuclear energy to the intermittent renewables and variable consumers. Some future research directions are given as follows:

(1) Interconnection Modeling

Based upon the recent advances in mechanism-based dynamical modeling, it can be seen that the composition of nuclear plants is more sophisticated than before. For the multimodular nuclear plants, there are multiple NSSS modules and even several thermal load equipment including not only the turbine-generator but also the cogeneration processes. Although there have already been many results in the dynamical modeling of NSSS modules, steam turbines, synchronous generators and cogeneration processes for hydrogen production, seawater desalination, etc., there is limited study on the dynamical modeling of the interconnection amongst multiple NSSS modules and thermal load equipment. Figure 5 gives the possible interconnections among different systems and equipment in a multimodular mHTGR plant, from which it can be seen that the interconnection is mainly given by the heat and mass transfer networks in the primary and secondary loops. In [4,83,84], the interconnection amongst multiple NSSS modules was modeled as a fluid flow network (FFN). However, the FFN can only describe the hydraulic interconnection. Since there must be thermal interconnection amongst multiple NSSS modules and thermal load equipment, the dynamical modeling of FFN with the exchange of both heat and work should be of concern in the future. For simulation, the interconnections can be described by lumped-parameter or distributed-parameter models, depending on the requirement on the level of detail in the simulation. For control design, since a complex design model gives a complex control law, the adoption of lumped-parameter models is recommended.

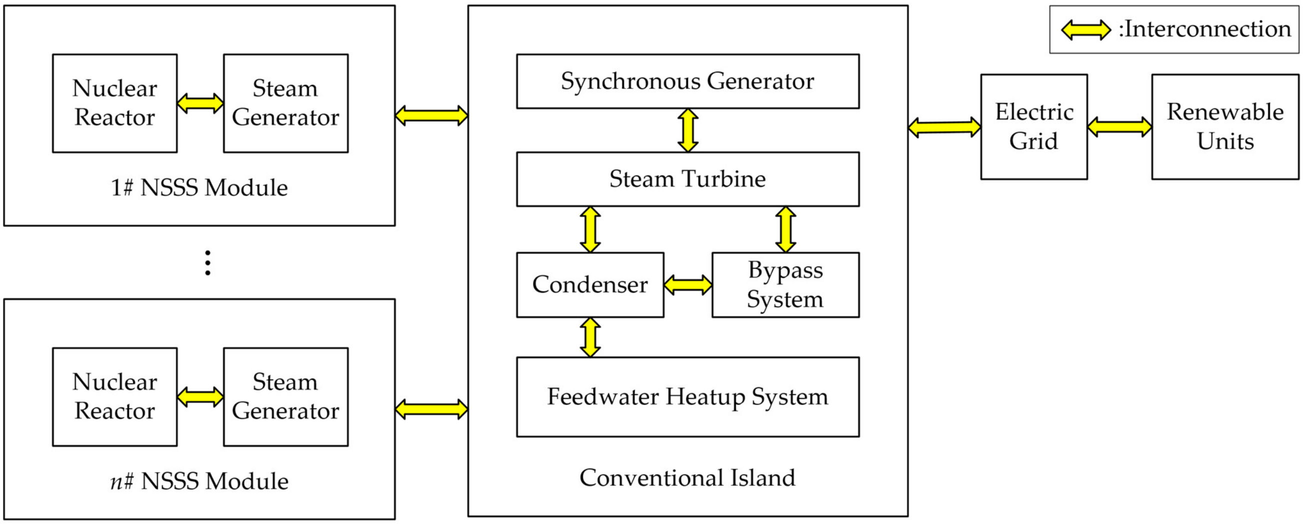

Figure 5. Interconnection amongst systems and equipment of a multimodular mHTGR plant.

(2) Joint Estimation of Parameters, States and Disturbances

The state-observers such as the Kalman filter, SMO, DHGF and ESO reviewed in Section 2.3 can provide the estimation of state-variables or even the joint estimation of state-variables and total disturbances. However, the internal parameters such as the temperature feedback coefficient, heat capacity and heat transfer coefficient are still obtained by the use of parameter estimation methods such as the least square estimator and the ridge estimator. For efficient monitoring and control of nuclear plants, it is necessary to give the joint estimation of parameters, state-variables as well as internal and external disturbances, where the difficulty lies in the structural design of the estimator and in guaranteeing the asymptotic convergence of estimations.

(3) Intelligent Nonlinear Control

From the review of intelligent control methods given in Section 3.1, it can be seen that the current control intelligence is mainly given by the approximation of nonlinear reactor dynamics by a set of local linear models and a fuzzy set or neural network for bonding the local models. It can be also seen that although the nonlinear reactor control law can be able to provide globally asymptotic or bounded stability, the stability is given for the nominal model without any uncertainty. Due to the online learning capability of neural networks and fuzzy sets, it is meaningful to combine nonlinear control methods such as the SMC, FLC and PBC with artificial intelligence to further improve the closed-loop robustness and adaptation.

(4) Online Control Optimization

Due to the intermittent renewables and stochastically various energy consumption, the steady-state operating points of nuclear plants are not constant anymore, which should be adjusted frequently according to the net load. To enhance the operational economy of nuclear plants, it is necessary to develop the online control optimization method. Though MPC methods can provide online optimization functions, the prediction model given by process mechanism or dynamical matrices should be provided. The reinforcement learning control method [47–49] is promising in the online control optimization, where the difficulty is to avoid the chattering or oscillation effect during the online recursive optimization procedure.

(5) Coordinated Control of the Nuclear and Renewables

Carbon neutrality is crucial for the sustainable development of human beings. Both the nuclear and renewables such as the wind and solar are important clean energy sources, where the nuclear can supply clean heat and electricity continuously with a large amount Due to the strong complementarity between the nuclear and renewables, it is meaningful to develop coordinated control methods of the nuclear plants and the renewable units in an energy mix. This coordinated control can deepening the penetration of renewables, and the excess steam provided by the nuclear plant can be used for chemical production such as seawater desalination, natural gas reforming and hydrogen production.

In summary, nuclear fission energy can be applied for the generation or cogeneration of electricity and chemical products such as hydrogen, potable water, etc., being an indispensable clean energy supplier in the energy mix. Modeling and control is an important part of nuclear energy technology, which not only describes plant dynamics from process mechanism and/or operation data, but also guarantees closed-loop stability, expected steady operating points and satisfactory transient responses based on proper control design. With the development of SMR and the requirement on flexible operation, some advanced results have recently been given in nuclear plant modeling and control. In this paper, the promising progress made in recent years is reviewed in detail, which shows that the tight combination of process dynamics and operation data is able to further enhance the monitoring and control performance of nuclear plants in the context of flexible operation. Some meaningful future directions, including interconnection modeling, joint estimation, intelligent nonlinear control, online control optimization and nuclear-renewable coordinated control, are then suggested. One more suggestion is that it is helpful to learn from the advanced results in some other areas, such as modeling and control in chemical engineering and biology.

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Nomenclature

ADP	Adaptive Dynamic Programming
ANN	Artificial Neural Network
BP	Backpropagation
CCS	Coordinated Control System
DAS	Differential Algebraic System
DBN	Dynamic Bayesian Network
DHGF	Dissipation-based High Gain Filter
DL	Deep Learning
DMC	Dynamic Matrix Control
DNN	Deep Neural Network
EEMD	Ensemble Empirical Mode Decomposition
ESO	Extended State-Observer
FDI	Fault Detection and Isolation
FFN	Fluid Flow Network
FLC	Feedback Linearization Control

FLI	Fuzzy Logic Inference
HCPS	Human-Cyber-Physical System
HEN	Heat Exchanger Network
HIL	Hardware-In-the-Loop
HJB	Hamilton–Jacobi–Bellman
HPH	High Pressure Heater
HTE	High Temperature Electrolysis
HTGR	High Temperature Gas-cooled Reactor
HTR-PM	High Temperature Gas-cooled Reactor Pebble-bed Module
IPK	Inverse Point Kinetics
LPH	Low Pressure Heater
LPV	Linear Parameter Varying
LQG	Linear Quadratic Gaussian
LS	Least Square
LSTM	Long Short Term Memory
LTR	Loop Transfer Recovery
MCC	Multimodular Coordinated Control
MLP	Multilayer Perception
MPC	Model Predictive Control
MSR	Molten Salt Reactor
NCP	Nuclear Cogeneration Plant
NPP	Nuclear Power Plant
NSSS	Nuclear Steam Supply System
ODE	Ordinary Differential Equation
OTSG	Once-Through Steam Generator
PCA	Principle Component Analysis
PDE	Partial Differential Equation
PHF	Port-Hamiltonian Form
PID	Proportional-Integral-Differential
PSO	Particle Swarm Optimization
PV	Photovoltaic
PWR	Pressurized Water Reactor
RBF	Radial Basis Function
RLC	Reinforcement Learning Control
RNN	Recurrent Neural Network
SC	Soft Computing
SISO	Single-Input-Single-Output
SMR	Small Modular Reactor
SMC	Sliding Mode Control
SMO	Sliding Mode Observer
ST	Super-Twisting
UKF	Unscented Kalman Filter
UTSG	U-tube Steam Generator
eMPC	Explicit Model Predictive Control
iPWR	Integral Pressurized Water Reactor
iRLC	Integral Reinforcement Learning Control
iSMC	Integral Sliding Mode Control
mHTGR	Modular High Temperature Gas-cooled Reactor
nMPC	Nonlinear Model Predictive Control

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