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A Grey-Box Digital Twin-based Approach for Risk Monitoring of Nuclear Power Plants

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Digital Twins (DTs) can enable real-time monitoring for improved risk assessment and tailored predictive maintenance of Nuclear Power Plants (NPPs). However, typical DTs are based on black-box models and their application is difficult to accept for such safety-critical systems. In this paper, we propose a grey-box DT comprised of: *i*) a real physical asset whose data/information is gathered from condition monitoring systems; *ii*) a dynamic white-box model of the NPP; and *iii*) a feedback loop that retroacts on the real asset. The grey-box DT-based approach is exemplified in a case study concerning a small modular dual fluid reactor (SMDFR) to show its applicability in NPPs.

Keywords: Digital twin, risk monitoring, grey-box modelling, nuclear power plant, dual fluid reactor.

1. Introduction

Nuclear Power Plants (NPPs) can contribute to clean energy transition (Cardin, Zhang, and Nuttall 2017). Their safety can be enhanced with condition-informed risk assessment models (Zio 2018; Di Maio, Antonello, and Zio 2018) that can exploit the plant state indications that are coming from the real-time monitoring of the components, whose outcomes can be used for risk-based and tailor predictive maintenance (Zio 2018; Compare, Baraldi, and Zio 2020; Lu, Baraldi, and Zio 2020; Kochunas and Huan 2021; Zhang, Qi, and Tao 2022).

Digital Twins (DTs) can enable real-time system performance monitoring with feedbacks to improve system reliability (You et al. 2022; Kochunas and Huan 2021). DTs have been successfully implemented for several purposes in different contexts, including critical infrastructures monitoring, smart cities, smart grids, power plants control, and manufacturing process optimization (Fuller et al. 2020; Gong et al. 2022). With respect to their application to NPPs, DTs can help decision-makers gaining a deep understanding of the physical processes to avoid critical errors during operation (Lin, Bao, and Dinh 2021). In this view, DTs can assist NPP real-time risk monitoring.

Nevertheless, DTs application in NPPs is challenged by the need of modelling nuclear reaction kinetics and dynamics, complex nonlinear thermohydraulic dynamics, and control disturbances, by combining information derived from simulation models, parameter-dependent partial differential equations, and data gathered from sensors for condition-monitoring components and systems. This results in a computational burden that may affect the real-time state prediction of the components and the real-time risk monitoring (Tidriri et al. 2016;

Gong et al. 2022).

To name few of the attempts done to develop DT-related tools in support to NPPs operation, Mori et al. (2005) developed a method to estimate reactivity parameters using a first-principle model, Promsylov et al. (2019) proposed a hybrid model that merges information from sensors and physical models for security assessment against cyber threats, Gong et al. (2022) simulated a Pressurized Water Reactor (PWR) dynamics with a physics-informed model, Di Maio et al. (2019) proposed a simulation-based method to compute the Goal Tree Success Tree Master Logic Diagram (GTST-MLD) for the risk analysis of cyber-physical systems, presenting an application on a nuclear lead-cooled fast reactor. However, none of these explicitly addresses the real-time feedback feature of a tailored DT for risk monitoring of NPPs (Jharko 2021; Kochunas and Huan 2021; Lin, Bao, and Dinh 2021). This is the research gap that we seek to cover in this research work.

For this, in this paper we present:

(i) A conceptual framework that satisfies the main requirements of a DT, that is, the incorporation of a real-time feedback loop between the physical object and the corresponding digital object;
(ii) A grey-box (GB) DT-based approach to consistently combine White-Box (WB) models for neutronic and thermohydraulic equations and Black-Box (BB) data-driven models for real-time risk monitoring.

The GB DT-based approach is exemplified on a case study concerning a small modular dual fluid reactor (SMDFR), originally presented in (Liu, Luo, and Macián-Juan 2021).

The remainder of the paper is organized as follows: Section 2 lays down the fundamentals for the development of a GB DT-based approach for risk monitoring. Section 3 presents the proposed GB DT-based approach for risk monitoring of NPPs. Section 4 presents the application of the proposed GB DT-based approach to the case study. Finally, Section 5 presents the concluding remarks and future work.

2. Background

2.1. Digital-Twin

In line with Fuller et al. (2020), a DT consists in an integrated model of a physical object, which is the real physical system, unit, or isolated component to be modeled, and the digital object, which models the physical object dynamics and predicts its state (You et al. 2022). We can, therefore, define:

(i) Digital Model: a model that lacks of automatic and bi-directional data exchange between the physical object and the digital object;
(ii) Digital Shadow: the digital representation of a physical object, comprising a one-way feedforward communication from the physical object to the digital object;
(iii) Digital Twin: the integrated model that considers the on-line data flow from the

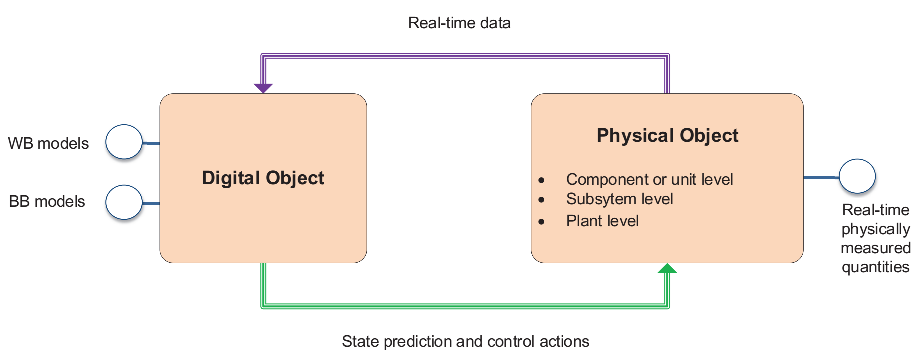

Fig. 1. DT real-time closed feedback loop modelling. BB: Black-Box; WB: White-Box.

existing physical object to the digital object and *vice versa*, generating a feedback loop (see Fig. 1) and full real-time integration between the two: while the physical object feeds the digital object with real-time data, the digital object processes it by the use of either WB or BB models to predict the future state and perform control actions over the physical object (Fuller et al. 2020). The main features of a DT are, thus:

- Bi-directional communication between the physical object and the digital object;
- Dynamic nature, that makes it evolving and adapt to the physical object that feeds the data automatically along the whole lifetime.

2.2. The digital object: modelling approaches

2.2.1. WB and BB modelling

Models are typically classified with respect to either the physical knowledge-dependence or the use of data to model system behavior (Loyola-Gonzalez 2019; Pintelas, Livieris, and Pintelas 2020): WB models, also known as physics-based models, depend exclusively on the physical knowledge, establishing a trade-off between accuracy and interpretability (Rai and Sahu 2020); conversely, BB models, also known as data-driven models, use and process data at the expense of direct interpretability and, therefore, expert-based understanding of the model output (Pintelas, Livieris, and Pintelas 2020). However, although WB models usually enable precision and extrapolation capabilities, they often bring high computational costs (Gong et al. 2022); BB models, on the contrary, can have low computational cost but poor extrapolation capabilities, depending on the training data provided that may be not fully consistent with the physical behavior of the system in all operating conditions (Rai and Sahu 2020).

2.2.2. GB modelling

GB models combine WB and BB models to overcome their limitations by trading off the model accuracy, the computational burden and the interpretability of the results (Rai and Sahu 2020). Indeed, they can be tailored to the physical system requirements and expected functionalities (Zendehboudi, Rezaei, and Lohi 2018).

3. The GB DT-based approach for risk monitoring of NPPs

Few examples of DTs are available in the

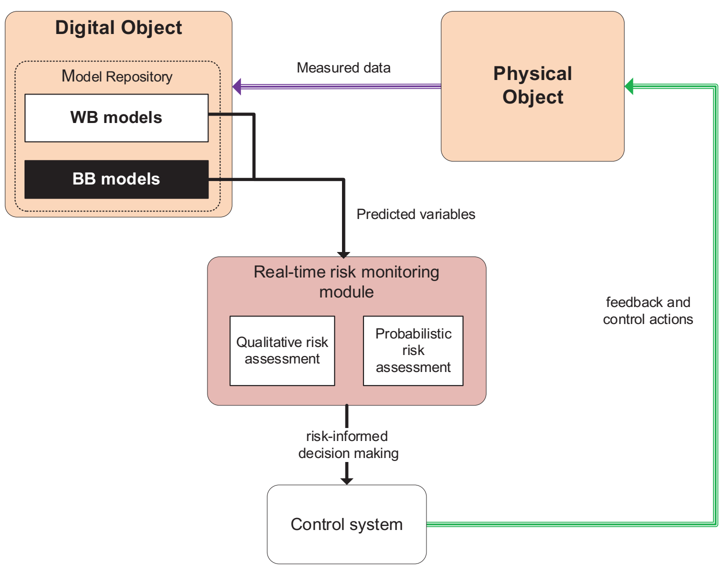

Fig. 2. Interactions between the digital and the physical object in a DT for risk monitoring applications

literature for applications related to risk assessment and management of industrial facilities (Agnusdei, Elia, and Gnoni 2021). To the authors knowledge, no DT approaches have been presented for NPP risk monitoring, for which specific technical requirements are defined by regulatory authorities (see Nuclear Energy Agency 2004, U.S. Nuclear Regulatory Commission 2016). Such technical requirements comprise aspects like the following ones:

- The risk monitor must provide tailored information derived from the application of qualitative and quantitative risk assessment techniques. In the case of quantitative risk assessment, the use of probabilistic risk assessment (PRA) techniques is encouraged in nuclear regulatory protocols and policies;
- Instantaneous or average estimates for standard indicators such as the core damage frequency (CDF) or large early release frequency (LERF) should be used under potential accidents, including external as well as internal initiators;
- The risk monitor should provide information in three timeframes: historical records (risk profiles and cumulative risk), instantaneous risk indicators, such as the current plant configuration and estimations of point-in-time risk, and predictions of the future state of the NPP;
- The risk monitor must ensure fast computing times (i.e., response time between 1 and 5 minutes) to ensure the effectiveness of the risk-informed decision-making process under all operating conditions.

In consideration of these technical requirements, we propose the GB DT-based approach for risk monitoring shown in Fig. 2: the physical object (i.e., the NPP) feeds the digital object (i.e., the digital model repository) with real-time data of monitored plant parameters (e.g., coolant inlet temperature, mass flow rates and heat transfer coefficients); conversely, the digital object delivers real-time values for several plant variables by compiling WB and BB models from the model repository (Kerlin and Upadhyaya 2019). Within this model repository, WB and BB models interact and interchange information to deliver the predicted variables of the NPP. These variables feed a combination of qualitative and PRA techniques to provide real-time risk monitoring and decision-making indicators for NPPs, such as the instantaneous CDF and LERF values (Nuclear Energy Agency 2004).

The risk-informed decision-making process results in a set of actions on the control system in compliance with the safety protocols and guidelines. In this way, the control actions close

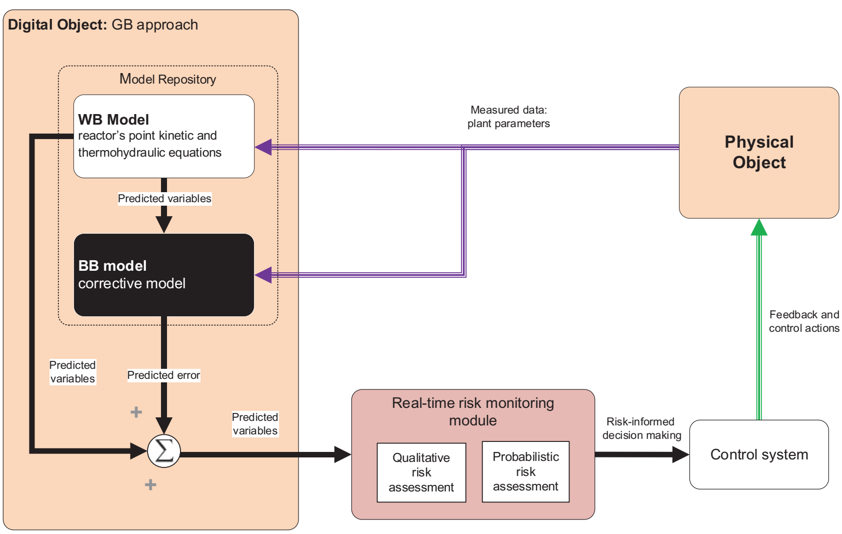

Fig. 3. Parallel GB DT approach for risk monitoring

the feedback loop communication between the physical and the digital objects, thus establishing the DT integration and bi-directional communication flow.

3.1. The digital object topology

Fig. 3 presents the topology of the digital object, when a parallel arrangement of the models is adopted therein: the WB model (i.e., a reduced-order physics-based model or a lumped parameter reactor core model) delivers real-time prediction of the actual physical variables values to preserve the underlying physical and causal relationships of the physical object; these feed the BB model, which in turn delivers an error prediction of the WB model to correct the predicted variables values; the combination of the BB predicted error with the predicted values of the WB model is, thus, expected to increase the accuracy of the predicted variables to monitor the risk and decide the control actions with increased confidence.

The parallel topology of the digital object model is useful when a reliable WB model of the system is available. In other cases, i.e., when some assumptions regarding thermodynamical properties and parameters are to be done (for example, fuel and coolant mass flow rates, and heat transfer coefficients are too uncertain), this topology may lead to low accuracy of the GB predicted variables because of the poor performance of the WB model. In this case, a series topology of the digital object (in which the WB and the BB models are arranged in series) would be beneficial, since, in such configuration the BB model predicts the uncertain or critical parameters of the WB model to improve its accuracy (see Naghedolfeizi 1990).

4. Case study

4.1 SMDFR models specifications

The GB DT-based approach is here exemplified with reference to the risk monitoring of a SMDFR, whose structure is shown in Fig. 4 (Liu, Luo, and Macián-Juan 2021): the secondary coolant captures the heat produced within the molten salt fuel, and brings it to the heat exchangers and the conventional secondary loop (Lewitz et al. 2020).

For the purposes of the presentation of the approach, the physical SMDFR is here simulated by a high-resolution model (Eltosohy et al. 2020). We consider a parallel arrangement of the models within the digital object (Fig. 3). A one-dimensional lumped-parameter model of the actual reactor core dynamics is taken as the WB model in the model repository, made of the point kinetic and the thermohydraulic equations needed to describe the temperature profile and the normalized power inside the core (Liu, Luo, and Macián-Juan 2021). Only two coolant nodes and two fuel nodes are considered, thus reducing the number of differential equations in the system to be solved (Vajpayee et al. 2020).

The technical requirements to consider when developing and implementing the GB DT-based approach for the SMDFR risk monitoring are:

(i) Fast computing times for delivering real-time values of the reactor core variables (neutron density, normalized power, and primary and secondary coolant temperature profiles);
(ii) Sensoring of thermohydraulics variables, such as mass flow rates, fuel and coolant inlet temperatures, and others;
(iii) Real-time computation of risk indicators by the systematic application of qualitative and quantitative PRA techniques tailored on the SMDFR.

To address the inaccuracies of the values of the SMDFR variables predicted by the lumped

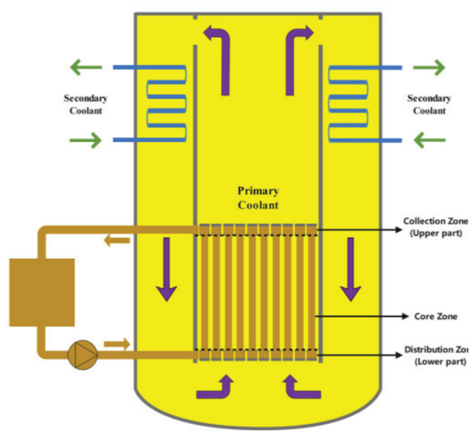

Fig. 4. Scheme of the SMDFR (Liu, Luo, and Macián-Juan 2021)

model, a BB model (for example, an Artificial Neural Network (ANN)) can be introduced for matching the variables values predicted by the WB model and the BB predicted errors with the high-resolution model values, thus increasing the accuracy of the GB output variables (Bontempi, Vaccaro, and Villacci 2004; Yang et al. 2017).

4.2 Real-time risk monitoring module

The developed GB DT-based approach can be used to dynamically assess the risk during the SMDFR operation, whenever it deviates from the nominal conditions and control actions are needed to recover normal functioning.

In the case of automated control devices (e.g, power control), a proportional-integral-derivative (PID) controller can be used to stabilize the system when the deviation is of low magnitude; otherwise, manual and complex control operations must be implemented on the basis of the decisions taken, informed by the risk indicators provided.

5. Conclusions

In this paper, we have presented a framework for the development of a GB DT-based approach for risk monitoring of NPPs, in a way to respond to the practical and regulatory requirements. To be effectively applied, the DT framework needs to be equipped with techniques and methodologies capable of debugging possible inconsistencies within the massive amount of data collected by sensors, that might affect the final overall performance of the risk monitoring module. Also, it requires a rigorous uncertainty quantification of the risk indicators values to ensure the fidelity and accuracy of the actions informed by them.

Future work will focus on: *i*) the actual implementation of the GB DT-based approach for the SMDFR case study and the analysis of the quantitative results; *ii*) the development of a multi-layer GB DT-based approach for risk and security monitoring of NPPs.

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