METHOD ARTICLE

Digital twin-driven intelligent maintenance decision-making system and key-enabling technologies for nuclear power equipment [version 1; peer review: awaiting peer review]

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Abstract

In the life cycle of nuclear power equipment (NPE), the long-term high-safety maintenance services play a vital role in ensuring their optimal operation. However, as the complex system equipment with high-safety requirements and high costs, there are lots of limitations of traditional time-based maintenance strategies for NPE. For example, the maintenance service process is invisible, the condition monitoring is mainly based on manual inspection, and the maintenance decision-making mainly depends on personal experience passively. Digital twins (DT) are an effective way to break the "information isolated island" in the whole life cycle, which can give full play to the value of data to realize the visualization of operation process of NPE. Nevertheless, nowadays, the application of DT in the field of nuclear industry is at the exploration stage, and there is lacking systematic and practical research. Thus, a novel DT-driven intelligent maintenance decision-making system involving three key-enabling technologies is proposed in this paper. Firstly, the DT-driven maintenance service mode is introduced, and its corresponding system framework is built. Then, the key enabling technologies such as DT modeling, condition monitoring and dynamic pre-alarm, and systematic intelligent maintenance decision-making and verification are expounded in detail. Finally, the cooling water pump is regarded as the case to verify the proposed method. The DT prototype system is developed and verified in the novel system, which demonstrates the novel system and the three key-enabling technologies are feasible and practical.

Keywords

Digital twin; Circulating water pumps; Intelligent maintenance service; Maintenance decision-making; Nuclear power; Cooling water pumps
Introduction
As a kind of renewable clean energy, nuclear power plays an important role in global carbon emission control. For example, in 2020, Pennsylvania’s nuclear power plants (NPP) prevented more than 46 million metric tons of carbon emissions which is equivalent of taking nearly 10 million cars off the road. According to the federal government’s evaluation, the saved social cost of carbon is more than $2.4 billion annually. Good maintenance will be able to minimize loss of production, reduce the cost of electricity generation, and reduce the risk. However, NPP is a conservative industry that is usually strictly regulated. Although there are so many models, methods, and strategies have been proposed, only a few have been applied for real NPP maintenance activities. Most of the NPP in the world are using the traditional approach, which results in high time-demand and low efficiency. Once an abnormality occurs, the operator needs to analyze the anomaly and find out the cause of the abnormality, to take timely measures to mitigate the impact of the fault and ensure the safe operation of NPP, otherwise, it will cause huge losses and impacts. According to the statistics, in NPP, the maintenance cost accounts for about 66% of the operating cost, and the cost of daily shutdown loss is $1.5 million. Therefore, designing an accurate and complete condition monitoring system to assist the operator in timely and accurately determining the state of NPP, which is of great significance for reducing the occurrence of operational accidents. It is urgent to explore and improve sustainable intelligent technology of maintenance service for NPE.

Digital twin, defined as an integrated multi-physics, multi-scale, probabilistic simulation of an as-built product, system, or process which can mirror the life of its corresponding twin using available physical models, history knowledge, and real-time data, is nowadays regarded as the key for the convergence of physical systems and cyber systems. In fact, with the development of global intelligent manufacturing, the countries leading in the nuclear power industry have carried out a large number of in-depth integration research on information technology and continuously introduced digital and intelligent information technology. Intelligent nuclear power is the trend of NPP. For example, in 2018, the Massachusetts Institute of Technology (MIT) carried out interdisciplinary research involving many researchers and released the report ‘The Future of Nuclear Energy in a Carbon Constrained World’. The report proposes that it is necessary to increase the use of virtual reactor and DT technology, and suggests adopting the method of integrating computer simulation and modeling to shorten the development process by 10–12 years. Siemens issued the white paper ‘The Virtual Nuclear Reactor’, which illustrates the value and potential of DT applied to nuclear reactors through three examples; In May 2020, the U.S. Department of Energy announced that as part of the planning of “Generating Electricity Managed by Intelligent Nuclear Assets, (GEMINA)” of the advanced energy research program, it would provide $27 million for 9 projects. These projects are dedicated to developing DT technologies, to reduce the operation and maintenance (O&M) costs of the next generation NPP by 90%.

The above literature shows the application of DT in the nuclear industry has drawn great attention, but the relevant theories and technologies supporting its application are still lacking. Consequently, the previous works for the applications of DT in intelligent maintenance and NPE will be given in the next section.

Related works
DT-driven intelligent maintenance
In terms of intelligent maintenance, DT can incorporate predictive models that evaluate the current state and after, analyze its behavior and predict the degradation of the component. Yu et al. proposed a DT-based decision analysis framework for the O&M of tunnels. The framework defines an extended construction operations building information exchange (COBIE) standard-based organization method for the tunnel twin data and uses Semantic web technologies to achieve fusion at the data, object, and knowledge levels. To improve the effect of predictive engine maintenance, Xiong et al. studied the aero-engine predictive maintenance framework driven by DT, and the implicit DT model is mined. Khazaeli et al. presented a multi-degree of freedom torsional model of the drivetrain system as the DT model for monitoring the remaining useful lifetime of the drivetrain components. To implement the predictive maintenance planning on the performance-based proactive service offerings for complex multi-component systems, Chang et al. presented a service-oriented dynamic multi-level predictive maintenance grouping strategy and one original equipment manufacturer (OEM) and multiple service provider’s multi-player maintenance grouping strategy. To solve the problem that the traditional centralized systems or platforms lead to the reluctant cross-organization knowledge sharing for each stakeholder, Chang et al. focused on the service-oriented maintenance decision-making (SOMD) processes and innovatively proposed a decision-making oriented collaborative knowledge sharing framework and multi-channel distributed blockchain network MKShareNet.

DT in the nuclear industry
For the application of DT in the nuclear industry, Nguyen et al. suggested that automating the task of fault detection and diagnosis is crucial in the effort to reduce O&M costs. They described a physics-based approach for the system-level diagnosis in thermal-hydraulic systems in NPP. Arzhaev et al. proposed that DT is an effective tool for NPP comprehensive data collection, management, and recordkeeping during long-term operation. In Floating Nuclear Power Plants, Kaiyu L et al. proposed a technical route of the DT. The design data is integrated and used to develop a DT system for nuclear fuel handling cabins. Based on the object linking and embedding (OLE) for process control unified architecture (OPC UA) communication protocol, the two-way interaction between the virtual cabin model and the control
system is realized. Ayo-Imoru et al.\textsuperscript{23} presented the framework for DT in a nuclear plant, which combines the application of the nuclear plant simulator and machine learning tools. They believed that DT can be employed to monitor plant conditions, fault diagnosis, prediction, and plant maintenance support systems. Kochunas et al.\textsuperscript{26} defined the DT of nuclear power systems, and then expounded the key challenges to realize the DT. Cancemi et al.\textsuperscript{27} believed that the lack of available data has slowed the development in the field of nuclear. To solve this problem, they proposed a new maintenance strategy based on the DT concept, suggesting that the machine learning (ML) algorithm can predict the behavior of the component, considering the operational and environmental conditions, and the aging ones. To better predict the behavior of NPP, Hu et al.\textsuperscript{28} introduced the classification, principle, and characteristics of data-driven machine learning (DDML), and elaborated its application research on NPE.

The above related works illustrate that the application research of DT in intelligent maintenance and NPE have yielded some results. However, the study for the feasible and practical application of DT in intelligent maintenance of NPE is still in its infancy. Moreover, in the nuclear industry, there are few academics pay attention to the systematics study from modeling, monitoring, and pre-alarm to intelligent maintenance decision-making.

To bridge this gap, a novel DT-driven intelligent maintenance decision-making system for NPE is proposed in this paper. The key enabling technologies and technical roadmaps are presented, which provided effective solutions for the unaddressed issues caused by traditional time-based maintenance strategies for NPE. In addition, the cooling water pump is taken as the research object, and the DT prototype system is adopted to demonstrate the feasibility of the proposed approach.

\textbf{Methods}

\textbf{DT-driven intelligent maintenance service mode}

According to the DT five-dimensional model\textsuperscript{29}, the DT-driven intelligent maintenance service mode for NPE can also be divided into five parts. As shown in Figure 1, it consists of five parts: physical NPE, virtual NPE, data and knowledge space, service system, and connection system.

As the physical entity, NPE is not only the carrier of the DT-driven maintenance service mode, but also the place where it is finally applied. NPP is a complex system, including material flow, energy flow, and information flow.

The above flow is transferred to the database, where the data are stored and preprocessed. Consequently, with the data and model integrated and fused, the knowledge for maintenance decision-making is generated by machine learning algorithms, which are stored in the knowledge base.

On the one hand, after the knowledge base is established, the virtual NPE can obtain the required information from the database or the knowledge base. On the other hand, the virtual NPE can, in turn, realize data monitoring and operation control for the physical NPE by a connection system. Therefore, the closed-loop perception and control between the physical entity and virtual entity of NPE are realized. After the above steps are finished, the intelligent maintenance service system of NPE is built, which can realize visual display of operation process, condition monitoring and dynamic pre-alarm, and proactive maintenance strategy decision-making as well as verification simulation.

\textbf{System framework}

From the perspective of function implementation and application service, this paper establishes a reference framework for the DT-driven intelligent maintenance decision-making system of the NPP, which includes the physical layer, virtual layer, and service application layer. The specific framework is shown in Figure 2.

\textbf{Physical Layer}. The physical layer refers to all facilities of the field environment, which includes key equipment, detection device, data processing hardware, and other physical entities in NPP. The field key equipment can be a subsystem or the key components of the NPP, such as the cooling water pump, which are the main object of the system. Meanwhile, as the subsystem of NPP, the important components or position of the cooling water pump include the pump guide bearing, the gearbox, and the pump input and output can also be regarded as the key equipment. The detection devices include sensors, barcode recognition equipment, radio frequency identification (RFID) identification equipment, cameras, etc. They transmit the monitored data of key equipment to the data processing hardware. The data processing hardware is used for data preprocessing and temporary storage, such as sensor adapter and digital analyzer for data classification and data format conversion.

\textbf{Virtual Layer}. In the virtual layer, numerous data from the physical layer are transmitted to the database, such as field operation data, fault data, simulation data, etc. Model space consists of a geometric model, behavior model, and mechanism model. The geometric model is built by 3D modeling of key equipment. The behavior model is formed from the analysis of the operation process of key components, which makes it the high-fidelity simulation analysis capability at the component level. From the perspective of the system level, the mechanism model is created by analysis and definition of the operation process resources and capabilities for systematic equipment. With the establishment of database and model space, the knowledge that can guide maintenance decision-making is formed by data integration and model fusion. For example, the knowledge of historical maintenance experience can be obtained by the fault data features. There is other knowledge, such as maintenance standard documents, maintenance strategy evaluations, and maintenance schemes.
Figure 1. DT-driven intelligent maintenance service mode. This figure is an original figure produced by the author(s) for this article.

Figure 2. Reference framework of DT-driven intelligent maintenance decision-making for NPP. This figure is an original figure produced by the author(s) for this article. The pictures in Physical Layer are photographed from field environment, which are owned by China Nuclear Power Engineering Co., Ltd.
in the knowledge base, which is the basis of intelligent maintenance decision-making.

**Service Application Layer.** The above two layers lay the foundation for the DT-driven intelligent maintenance decision-making system, which is also the basis of the service application layer. In view of the defects of the traditional maintenance mode, the service application layer includes the functions of operation process visualization, condition monitoring and risk dynamic pre-alarm, intelligent maintenance decision-making, and remote maintenance.

Key-enabling technologies and roadmaps

Based on the above mode and framework, in this section, three key-enabling technologies and roadmaps are proposed to realize the novel system. They comprehensively adopt theories, technologies, or methods, such as 3D modeling, Modelica language, machine learning, deep learning, etc.

**DT modeling**

Model is not only a part of DT, but an important premise to realize DT functions. In response to the bottleneck problem for the current research and practice of intelligent manufacturing, Zhang et al. proposed the multi-dimensional and multi-scale intelligent space model of DT manufacturing cell (DTMC) and its high-fidelity modeling method. The prototype system of DTMC developed by Java web has great reference significance for the modeling method in this paper. The construction steps of DT modeling for NPE is shown in Figure 3.

(1) To build the geometric model of NPE, SolidWorks (Version:SOLIDWORKS 2021, Access: https://www.solidworks.com) software is used for 3D modeling, Pixyz Studio (Version: Pixyz Studio 2022.1.0.36, Access: https://www.pixyz-software.com/studio/pricing) software for lightweight, and Blender (Version: Blender 3.2, Access: https://blender.bgeach.com/download.html) software for format conversion and model rendering. On this basis, the dynamic and kinematic equations of each actuator are defined to support the accurate synchronization of the virtual and real operating conditions of NPE. The mechanism model of NPE is built by modeling languages, such as Modelica, systems modeling language (SysML), and MWorks. Webots (Version: 18 Dec 2021 - R2022a, Access: http://www.cyberbotics.com/) can be used to construct behavior models.

(2) Machine learning algorithms, such as neural networks and support vector machines (SVM) are used to establish the condition monitoring model of key equipment and the analysis model of operation conditions, which effectively supports the real-time analysis and control of key operational indicators. Then, the protocol analysis and fusion model of multi-source heterogeneous data are accomplished by open graphics library (OpenGL), and the model visualization is realized by the front-end technology based on Java web.

(3) Based on the open database connectivity (ODBC) or the java database connectivity (JDBC) interface technology, a unified data interface of the geometric model, mechanism model, and behavior model is constructed.

(4) OPC UA or message queue telemetry transport (MQTT) standard protocol is adopted to realize the data synchronization and exchange of unidirectional, bidirectional, and one-to-many among various models. On this basis, a multi-factor evaluation index system is constructed to evaluate and optimize the fidelity of the integrated model.

(5) The prototype system is developed by the front-end languages, such as HTML, CSS, JavaScript, Vue, element UI, etc. The real-time data is accessed to complete the operation and debugging of the prototype system.

Condition monitoring and dynamic pre-alarm

To realize the functions of condition monitoring and risk dynamic pre-alarm for NPE, on the basis of the above DT models, the concrete implementation process is divided into four parts: original data, data pre-processing, databases, and applications, as shown in Figure 4.

(1) As a complex system, there are numerous raw data in NPP, such as field operation data, fault data, simulation data, and other data, which present the characteristics with great variety and heterogeneity. Consequently, preprocessing the original data is necessary.

(2) Through data processing algorithms, such as Monte Carlo method, effective data sets are obtained from these original data. In the view of the functions to be realized in the end, the fault sample data set is mainly considered in this paper. With the effective data sets obtained, the standardized data is stored in the form of key-value pairs while the transmission format is standardized.

(3) In the process of data storage, the real-time data generated during the operation of key equipment with a unified format is stored in the non-relational database Redis, which will serve real-time condition monitoring and risk dynamic pre-alarm for NPE. Meanwhile, without affecting the real-time data storage and application, the relational database MySQL is used to save the historical data, which will serve the optimal maintenance decision-making for NPE.

Maintenance decision-making and verification

This key technology consists of three parts: knowledge-driven intelligent maintenance strategy automatic recommendation, data-driven multi-level optimization decision-making of maintenance time, and DT and mixed reality (MR)-driven visualize simulation verification of maintenance risk. The

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1 Alternative free software: FreeCAD 0.20 (Access: https://www.freecadweb.org/)
data-knowledge-simulation-driven intelligent maintenance decision-making method is formed in the end, which is shown in Figure 5.

With the database established, the dynamic knowledge base is built while the knowledge of O&M is acquired by the dynamic perception of NPE, which is also established by MySQL under the consideration of rapid growth and change of data during the operation process of NPE. After the mining of knowledge concepts and relationships in the dynamic knowledge base, the knowledge graph model is further built for maintenance decision-making of NPE.
The construction of a data-knowledge-driven intelligent maintenance decision-making method. This figure is an original figure produced by the author(s) for this article.

Based on dynamic knowledge base and knowledge graph model established, the maintenance decision-making model of repair, replacement, and overhaul depended on condition monitoring and risk pre-alarm is constructed. This model can realize the proactive recommendation service for the perceived fault information while it calls proactive knowledge service-engine under the condition of the corresponding intelligent contract is triggered by the perceived fault information from real-time data. Thus, the technology of knowledge-driven intelligent maintenance strategy proactive recommendation for maintenance decision-making is accomplished.

Based on the above technologies, the maintenance strategies need to be further evaluated, optimized, and verified. On the one hand, maintenance cost is the main factor in the intelligent maintenance of NPE. Therefore, it is necessary to establish a cost evaluation model to evaluate the cost of maintenance strategies under resource constraints. On the other hand, the selection of maintenance time is also a key factor to be considered. Consequently, it is necessary for all maintenance knowledge in the database to be trained by deep reinforcement learning to realize the optimization of maintenance time decisions at the part, component, and system level. Thus, the maintenance time obtained need to be further verified by the visual simulation to get the best one.

As mentioned above, the verification cases of the technology of DT-MR-driven visualize simulation verification come from the proactive recommendation in Figure 5(a) and maintenance time in Figure 5(b). As shown in Figure 5(c), the technology of DT-MR-driven visualization simulation verification consists of two parts: risk verification of maintenance activities and equipment failure. The risk verification of maintenance activities adopts the MR method to realize the complete maintenance process, including the steps of selecting maintenance personnel, replacement, installation, and debugging. The risk verification of equipment failure determines the best time of maintenance through the simulation of equipment status and the risk pre-alarm time.

Results
To intuitively verify the availability of the above key-enabling technologies, a DT prototype of a cooling water pump is formed based on the scaled-down test bed. As the key equipment, the cooling water pump plays a vital role in the normal operation of NPP. According to research, the impact of 1 °C increase in temperature of the coolant extracted from the environment is predicted to yield a decrease of 0 ~ 0.45 and 0 ~ 0.12% in the power output and the thermal efficiency of the pressurized-water reactor NPP considered, respectively. Therefore, the cooling water pump is taken as the main study case in this paper. In this section, the results will be illustrated in three parts: the environment of the case study, the prototype system development, and the application and verification of the prototype system.

Environment of hardware and software
Hardware environment. As mentioned above, the case study of this paper is aimed at the cooling water pump. The hardware equipment mainly consists of the cooling water pump, signal detection device, and hardware for data processing and storage, which is shown in Figure 6.
Figure 6. Environment of hardware. This figure is an original figure produced by the author(s) for this article. The pictures are owned by China Nuclear Power Engineering Co., Ltd.

Figure 6(a) is the whole system of the cooling water pump, which mainly consists of the main body of the pump, circulating water pipe, safety valve, and water tank. Figure 6(b) is the signal detection device. In this paper, various sensors are used as signal detection devices to detect the three key components or parts of the cooling water pump. The three key components are the pump slide bearing, the gearbox, and the pump inlet and outlet. As shown in Figure 6, the sensors used in the pump slide bearing and gearbox are displacement sensors, accelerometers, pressure sensors, and temperature sensors. In the pump inlet and outlet, flow and pressure sensors are deployed. Figure 6(c) is a multi-channel vibration control and testing instrument. There are many functions in it, such as data acquisition, real-time signal analysis, model testing, and condition monitoring. Therefore, it is used to store and analyze the data collected by the above sensors.

Software environment. For the construction of the software environment, this paper mainly introduces the front-end part. Based on the development of the visual studio code (VScode) editor, the model integration and visual display are realized by the front-end technologies, such as HTML, JavaScript, and CSS. It mainly includes three parts: model and condition display area, function selection area, and data visualization area.

Prototype system development
Based on the above key technologies, in this case, the geometric model is obtained by modeling, lightweight, and model format conversion and rendering. The import of the geometric model and the acquisition and definition of model components are completed by babylon.js. In fact, as a web visualization framework based on web graphics library (WebGL), Babylon.js provides many methods, such as model control, motion logic setting, and geometric model status updating. The mechanism model will be built by Modelica language, which provides simulation and analysis capability for the DT model, and then integrates it into the geometric model to simulate the operation process of the physical entity. The key parameters, such as flow, pressure, and temperature of the three components in the database and their dynamic change processes will be drawn using the echars.js visual chart library and embedded in the DT system. Based on this, the above model will be integrated into a visualization system depending on Java language and Browser/Server architecture.

Through the perception and control between the scale-down test bed and the prototype system, for the cooling water pump, the real-time monitoring, condition evaluation, and optimization feedback of the whole operation process will be realized to achieve intelligent maintenance decision-making. The specific process is shown in Figure 7.

Application exploration of a prototype system: the value that the method will add to the nuclear field
Based on the above environment configuration and the development of the prototype system, it’s necessary to explore
the application of the prototype system in the cooling water pump according to the service application layer in the system framework. **Figure 8** shows the front-end page of the DT model of the cooling water pump, which illustrates the following three applications will be realized.

**Operation process visualization.** Figure 8(a) is the condition display area of the DT model, where the key components and the operation process of the cooling water pump are visualized. In addition, Figure 8(b) shows the buttons, where the visualization of the angle and size of the model, and even the key equipment hidden in the shell can be controlled. Figure 8(c) is the data visualization area, where one can realize the visualization of real-time data for key parameters of pump guide bearing, gearbox, and the pump input and output.

**Real-time condition monitoring and dynamic risk pre-alarm.** As shown in Figure 8(a), the status of the field equipment will be judged by different colors in the DT model after the real-time connection between the scale-down test-bed and the prototype system realized. We can click the equipment in the DT model to observe and analyze the detailed information when the failure happened. If the fault reaches a certain degree, the equipment would be converted into another color for pre-alarm in the model, and the color will return to normal when the fault is removed. The above is the process of dynamic risk pre-alarm.

**Intelligent maintenance decision-making.** Firstly, we can judge the type, position, and severity degree of the fault through the DT model when the circulating water pump breaks down. Then, based on the database and knowledge base established for the circulating water pump and the key technologies mentioned above, the prototype system will proactively provide maintenance strategies for this fault. Finally, to obtain the optimal maintenance strategy, the feasibility of the maintenance strategies provided by the prototype system will be verified through simulation.

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**Figure 7.** DT prototype system and the scaled-down test bed. This figure is an original figure produced by the author(s) for this article. The picture is owned by China Nuclear Power Engineering Co., Ltd.

**Figure 8.** The application display of the DT model.
Conclusions and future work
This paper aims to provide an optimal maintenance decision-making proposal by introducing a DT-driven system for NPE. Aiming at the defects of traditional maintenance decision-making, several application services, such as online real-time condition monitoring, dynamic risk pre-alarm, and intelligent maintenance decision-making are given in the proposed system. The main contribution of this paper can be summarized as follows: (1) To figure out the research status of the application of DT in intelligent maintenance and NPP, the related works of the two fields are given respectively in this paper. (2) A DT-driven maintenance service mode is proposed to illustrate the application mode of DT in the maintenance of NPE. Meanwhile, to clarify the contents of this system in detail, a system framework is expounded, which consists of three parts and sums up the service applications from the function implementation. (3) Three key-enabling technologies and their roadmaps, namely DT modeling, condition monitoring and dynamic pre-alarm, and maintenance decision-making and verification, for supporting the system are analyzed. (4) Based on the scaled-down test bed, take the cooling water pump as the study object, a prototype system is developed to verify the effectiveness of the proposed system, and its environment of hardware and software are given in detail. What’s more, three application explorations of prototype systems in cooling water pumps are proposed to show the service functions that will be realized.

Although the prototype system has developed, there is only the front-end part, and many functions are still in the stage of theoretical exploration, such as the virtual-real parallel operation, real-time condition monitoring, and intelligent maintenance decision-making. Based on this, future work will be further studied with the following aspects: (1) We will finish the construction of the back-end of the prototype system based on Java technology. (2) We will finish the definition of the dynamic and kinematic equations of each actuator to realize the accurate synchronization of the virtual-real parallel operation of the circulating water pump. (3) To realize the online analysis and monitoring of key indexes of cooling water pump, we will accomplish online self-learning of database and knowledge base through transfer learning and incremental training algorithm. (4) Machine learning algorithms, such as neural networks and support vector machines (SVM) will be used to build a knowledge base and model for condition monitoring, fault diagnosis, and maintenance decision-making.

Data availability
No data are associated with this article.

Software availability
The underlying data and software code cannot be made publicly available because of the privacy policy of China Nuclear Power Engineering Co., Ltd, who sponsored and provided the technical support for all of the paid software and hardware used in this study. Due to trade secrets and company-related privacy policies, the data and code cannot be provided publicly. Interested readers/reviewers can contact Qian Huang via email huangqian@cnpe.cc to request access to the underlying data and code. Interested parties should provide a proposal of what they want to do with the data, and this proposal would need to be confirmed by China Nuclear Power Engineering Co., Ltd. Use for academic research purposes will be permitted, and any request for commercial use will be denied.

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