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Digital Twin and Its Application in Storage and Maintenance of Solid Rocket Motor

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Abstract:

With the development of the new generation of information technology, the digital twin has become the research hotspot in the field of complex equipment system design and operation and maintenance due to its virtual and real interaction characteristics. This paper summarizes the development of the concept of digital twin, concludes the connotation of digital twin on this basis, and summarizes the current research and application of digital twin. In order to solve the problem that the solid rocket motor's operation, maintenance and life evaluation are not closely combined with the motor entity and specific task requirements, this paper proposes to combine the digital twin technology with the solid rocket motor, discusses the frame structure of the solid rocket motor digital twin body, provides the overall design of solid rocket motor storage performance prediction based on digital twin, and the realization method is described in order to provide reference for the application of digital twin technology in storage maintenance and life evaluation of solid rocket motor.

***Keywords**: Solid rocket motor, Storage performance, Digital twin, Performance prediction.*

I. INTRODUCTION

Solid Rocket Motor (SRM) has many advantages such as simple structure, high reliability, convenient use and easy long-term storage [1]. As the power plant of missile weapon system, it has been widely used in both short-range tactical weapons and long-range strategic weapons. Due to the characteristics of long-term storage and one-time use of SRM, the evaluation of its storage state and the length of storage life determine the application prospect of SRM. Therefore, it has been a hot issue in the industry to design long-life SRM, accurately evaluate its current state and predict its storage life.

At present, the operation maintenance and life evaluation of solid rocket motor at home and abroad are mainly based on the technical indexes formulated at the beginning of motor design, and cannot be combined with the actual situation and specific task demand of the motor. The appearance of digital twin technology provides a new thinking and method for solving this problem. Digital twin includes physical entity and virtual model, and emphasizes the bidirectional interconnection between virtual and real. By building a high fidelity digital twin model for solid motor, collecting physical data such as motor state data, material attribute data and environmental monitoring data, effectively fusing twin data and expert knowledge base and other information data through bidirectional interconnection between physical entity and twin model, and dynamically updating twin model according to this, the performance change mechanism of solid motor in whole life cycle can be revealed from a deeper level, thus the comprehensive performance prediction method of solid motor based on digital twin can be constructed, and the deep fusion of big data, artificial intelligence and solid motor can be realized.

II. THE CONNOTATION OF DIGITAL TWIN

The concept of twin originated from the Apollo program of the United States in 1860s. [2] The idea is to build two identical spaceships, one is launched into space to perform a mission, the other is to simulate all the processes experienced by the actual flying spaceship on the ground, reflecting the actual state of the spaceship through the ground spaceship and providing reference data for the maintenance of the spaceship. This is the rudiment of the concept of twinning, which is called physical twinning, also known as physical companion flight.

The idea of Digital Twin was first put forward by Professor Grieves [3] of University of Michigan in his product life cycle management course in 2003. Corresponding digital isomorphs are established for physical products. The digital isomorphs are virtual digital representations equivalent to physical products, which contain all the information of physical products and mainly serve the whole life cycle management of products. The model consists of three parts: physical products, virtual representation forms of the products and bidirectional data connection between virtual and real, which are the three basic elements of digital twin, so the model is regarded as the embryonic form of digital twin. With the development of technology and continuous improvement of cognitive level, the understanding of this model has been continuously developed, from mirrored spaced model [4] to information mirroring model [5] , Professor Grieves [6] , in 2011, cited the word Digital Twin proposed by his collaborator John Vickers to replace the information mirroring model, which has been used up to now. The Digital Twin consists of physical space, virtual space and bidirectional interaction between virtual and real, and the bidirectional interaction between virtual and real includes data from physical product to virtual representation and information and process from virtual representation to physical product, which constitute a loop, as shown in Fig 1.

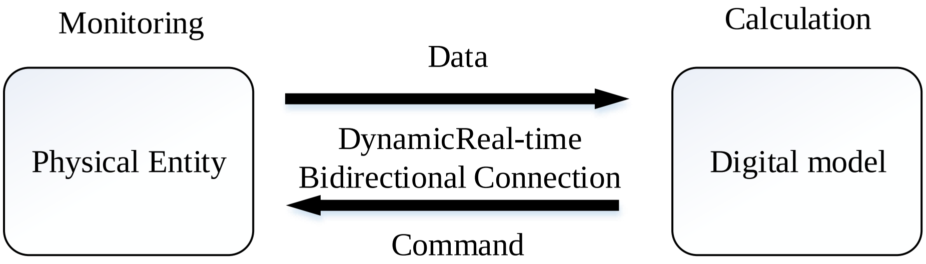

Fig 1: Bidirectional connection between physical entities and digital modes

Since 2010, with the rapid development of new generation information technology such as Internet of Things, big data, cloud computing, artificial intelligence, etc., people have constantly enriched the collection means of product-related information, virtual modeling and description of physical products have become more and more accurate, high-speed development of computer performance, algorithm and mobile communication technology has laid a solid foundation for big data processing and real-time data transmission, and people's research on digital twin has entered into a period of rapid development. Starting from their respective research fields, they combined relevant technologies of digital twin with specific research objects, elaborated their respective understanding and cognition, and gave different meanings to digital twin.

Professor Grieves [6], starting from the perspective of product life cycle management, believed that virtual product is an informational expression of physical products and relevant environment for a specific purpose, while information mirroring model is a conceptual management framework constructed within the whole life cycle of products, including rules, behaviors and meanings of physical products and virtual products. The value of the model is that virtual products can be used instead of physical products for simulation operation or test during the full life cycle of products. In view of the problems existing in periodic inspection and maintenance of aircraft fleet, NASA and USAF [7-8] define digital twin as a digital carrier tool integrating multiple physical fields and multi-scales. By constructing a high-precision model of the aircraft and combining the real-time monitoring data and historical flight data of sensors, the simulation analysis based on probability is carried out on the aircraft, so as to reflect the real situation of the physical aircraft. From the perspective of software, General Electric Company explains that digital twin is to express assets and business processes in the form of software, which is used to explain business processes and predict and optimize the execution process and performance so as to obtain better business results [9]. PTC Corporation interprets digital twin as a function composed of physical product, application service, data management and functions formed by connecting networks from the aspects of Internet of Things and Data Integration. Physical product is responsible for generating monitoring data, and application service realizes simulation function. Data management includes data calculation, data storage and data analysis. Connection network refers to network connection between physical product and application service. In their white paper on digital twin technology, Pera Corporation Ltd. and Digital Twin Laboratory choose to use the word digital twin to define the digital twin as the digital model corresponding to the physical entity. By monitoring the state data of the physical entity and analyzing the data, real-time perception and diagnosis of the physical entity state are carried out, simulation analysis is conducted on the physical entity based on the model and real-time data, the future state of the physical entity is predicted, optimization decisions and control instructions are generated to regulate and control the physical entity behavior. Each digital model continuously evolves through learning from each other, so that the decision-making within the life cycle of the physical entity is more optimized [10].

Based on the above definitions given by different institutions, it can be concluded that digital twin is the digital expression of physical products or systems, which means to construct a virtual system which can reflect and characterize the characteristics of physical equipment in the information space, which can reflect the status of physical products or systems in real time and dynamically, simulate, analyze and optimize physical entities so as to improve product operation performance and maintenance efficiency, at the same time, it can understand product quality problems and improve product design and manufacturing. The relationship between physical entities and virtual systems is not unidirectional or static, but rather closely linked throughout the product life cycle. To sum up, digital twin has the following connotations:

(1) The digital twin model does not exist alone, but must correspond to a physical entity to reflect the real state of the physical entity. If there is no physical entity, the digital twin model will lose its meaning of existence.

(2) The physical entity can be hardware products, such as motor casing, grain, etc., or software system or process, such as motor valve control system, grain creep process, etc.

(3) Each digital twin model has specific functions. In accordance with different functions, different digital twin models can be constructed for a physical entity, such as case digital twin model for solid rocket motor, bonding interface digital twin model, ignition build-up process digital twin model, steady state combustion process digital twin model and so on.

(4) The digital twin model should be based on the real-time data of the physical entity and faithfully reflect the real state of the physical entity. Moreover, the digital twin model should be ahead of the physical entity and be able to predict the future state of the physical entity effectively in accordance with the real-time data.

(5) There must be data interaction between the digital twin model and the physical entity. The state data of physical entity is the foundation of building digital twin model, and also the basis of predicting the future state of physical entity by digital twin model. The prediction result of digital twin model is also transmitted to physical entity and drives it to change its own state. Therefore, the data interaction between physical entity and digital twin model must exist and be bidirectional. This kind of data interaction can be online, offline, real-time or non-real-time.

III. RESEARCH STATUS OF DIGITAL TWIN

The austere idea and application of digital twin may be traced back to the sand table used in marching battles thousands of years ago. Friends who like to play games know that in many games you can build cities, form armies, arrange battle formations and so on in accordance with their own imagination, these can be regarded as the application of digital twin. In recent years, the development of computer, Internet of Things, big data, cloud computing, artificial intelligence and other new generation of information technology has provided technical support for the landing application of digital twin. Digital Twin combines artificial intelligence, machine learning and software analysis with data to create vivid digital simulation models, which update and change with the change of physical entities, and are widely used in many fields such as energy management [11-16], medical care [17-20], intelligent manufacturing [21-25], aerospace [26-33], etc.

3.1 Application of Digital Twin in Intelligent Manufacturing

Intelligent manufacturing is the most widely used field of digital twin at present, and it is also one of the earliest application fields of digital twin. At present, under the background of Industry 4.0, the major manufacturing giants are making vigorous efforts to carry out digital transformation and integrate digital twin into their own business practice, so as to form solutions in line with their own realities under Industry 4.0 system. BMW uses digital twin in the production of motor blocks, increasing production efficiency by 12% while reducing scrap rate by 25%. Volkswagen introduced the digital twin into the automobile battery system, which effectively improved the output efficiency and performance of the battery. Volkswagen ID. R created a good achievement of 7 minutes 38.585 seconds in challenging the 99-track curve of Tianmenshan [34] . Based on Leonardo platform, German SAP Company has constructed a complete set of product R&D software system based on digital twin, forming a closed-loop system of product R&D and optimizing the product best [35] . Tao Fei et al. [36-37] put forward the concept of digital twin workshop aiming at the interaction and communion between the physical world and the information world of manufacturing, systematically discussed the basic theory and key technology of realizing the physical information fusion of digital twin workshop from four dimensions of physical fusion, model fusion, data fusion and service fusion, providing reference for enterprises to practice digital twin workshop. In December 2019, China-Russia East Line Natural Gas Pipeline Project jointly constructed by CNPC and Gazprom was officially put into operation for ventilation. This project constructed a pipeline digital twin, integrated pipeline life cycle data, realized research, design, construction and operation under unified platform and data standard, and greatly improved the technology and management level of China pipeline industry [38] .

3.2 Application of Digital Twin in Smart City Construction

With the continuous growth of urban population and urban scale, modern cities have made new changes in urban function, urban form and management mode, especially the application of new generation of information technologies such as big data [39], Internet of Things [40], cloud computing [41], etc. has accelerated the development of this change. Nowadays, there are all kinds of sensors, cameras and other sensing devices all over the city to collect real-time state data of each aspect of the city. These data are transmitted to the corresponding twin models in the cloud through the Internet of Things. The twin models are updated automatically in accordance with the data and predict the future change situation, so as to realize the functions of real-time monitoring of the operation status of urban water, electricity, gas and transportation facilities and the allocation of various resources in the city etc. The digital twin city is formed by the integration of various digital twin models that realize different functions. It can be seen that the construction and management of modern cities are no longer independent among industries and regions, but become an organic whole with mutual integration and mutual communication [42]. In order to better realize the comprehensive governance of smart city, Wang Lianfeng et al. [43] established the system model and data model of smart city comprehensive treatment, providing reference for promoting the construction and development of digital twin cities. To keep up with the pace of urban digitization, all walks of life need to be transformed digitally, especially in the energy sector. Tang Wenhu et al. [44]

considered that digital twin technology is an effective means to solve the technical and market barriers faced by the current development of smart energy. Through summarizing the development experience of smart energy system at home and abroad, they respectively elaborated the general framework, key technologies and ecological construction of smart energy system based on digital twin, analyzed the deployment and application cases of digital twin technology in smart energy industry, and provided corresponding countermeasures and suggestions, providing reference for the application of digital twin technology in smart energy industry. The main body of urban construction service is human beings, so the goal of smart city construction and development is also for the better work and life of people. At present, the aging of population in China is becoming increasingly serious, and caring for the elderly has become an important aspect in the construction of smart city and smart community. Zhang Jie et al. [45] combined digital twin with visual sensor, artificial intelligence and depth learning to develop a real-time monitoring and alarm system based on digital twin technology for the elderly such as falling down, abnormal posture, etc., realizing the refined management of the state of the elderly in the community.

3.3 Combination of Digital Twin and New Infrastructure

The development of Smart City requires the construction of new supporting infrastructure. The new infrastructure is a new infrastructure construction system adapted to the modern economic and social system established by absorbing and borrowing the development achievements of modern science and technology under the promotion of the new development concept. Under the current economic and technical level, the new infrastructure mainly focuses on the new generation of high-speed network, big data, artificial intelligence, Internet of Things, new energy, high-speed railway and other fields. Applying digital twin technology to new infrastructure construction can change the cooperation mode of infrastructure project from design, construction to later operation and maintenance, solve the problem that data change cannot be fed back in the past, and enable the whole project team to get the latest data update in real time based on a data integration platform [46] . Data is the fundamental difference between the new infrastructure and the traditional infrastructure, so the construction of the data center is an integral part of the new infrastructure. The construction of digital twin data center is to realize panoramic reproduction of data center in virtual world through 3D [47], VR [48] and other technologies, collect status data of all asset objects such as environment, network and host of data center and integrate them into a unified visual platform, so that relevant management personnel can intuitively grasp the real-time status of data center operation. In view of the intelligent operation and maintenance problem of data center equipment and machine room infrastructure, Chen Qing [49] constructed corresponding digital twin model from three levels of machine room, refrigeration system and intelligent data center, and elaborated three application scenarios of machine room digital twin, refrigeration system digital twin and intelligent data center digital twin respectively, providing guidance for the ground application of digital twin technology in data center. In addition to the data, interconnection is also an important part of the new infrastructure. In order to better support the industrial development, transformation and upgrading of the communication system, Wang Jian et al. [50] combined the digital twin technology with the wireless communication channel, proposed the concept of digital twin channel for the first time, constructed the five-dimensional digital twin model of the wireless communication channel, studied and discussed the application system, functional system, technical system and standard system of the digital twin channel, with a view to improving the demonstration, design, development and testing capability of the 5G and 6G systems and provide beneficial reference for the communication engineering construction under the new system. With the rapid development of rail transit, the travel time cost of people is greatly reduced. The subway in cities and the high-speed railway between cities have become the first choice for most people to travel. Based on virtualization technology, the construction of digital twin rail transit is to display the status of stations, operation routes and equipment of rail transit in visual form, which is convenient for managers to manage and control and ensure the operation safety of rail transit. Based on digital twinning technology, Wang Hao et al. [51] established the three-dimensional digital twin model of CRH380BL EMU wheel set and carried out simulation, and studied and summarized the influence law of tread wear and rim wear on dynamic performance of wheel set, laying a foundation for digitalization of EMU wheel set in full life cycle. It is very common and frequent to use the relay in the office building, if an unexpected power outage is caused due to relay failure, the economic loss should be very huge. Phoenix Contact [52] introduced the digital twin technology into the relay and developed the digital twin relay, which can eliminate the risk of unexpected shutdown of tens of thousands of dollars per hour through predictive maintenance.

3.4 Application of Digital Twin in Aerospace

In 2010, the goals and application scenarios of digital twin were described in two technical roadmaps including digital twin modeling simulation and material structure issued by NASA. It was pointed out that the application of digital twin in the design, manufacturing and maintenance of aircraft can effectively reduce the maintenance cost and prolong the service life of the aircraft [7]. In order to solve the problems of aircraft maintenance and life prediction, the US Air Force put forward the assumption of establishing a digital twin fuselage for each aircraft to predict the future status of the aircraft [53]. Therefore, GE Research Institute uses digital twin technology to perform predictive maintenance for the aircraft based on reliability analysis. Compared with the original periodic maintenance, the number of maintenance times is significantly reduced under the premise of ensuring the mission success rate and the maintenance cost of the aircraft is reduced; while Northrop Grumman Company establishes a digital twin process model for the aircraft maintenance process, integrates the analysis method for crack propagation into the model, integrates and eliminates uncertainty factors therein, and improves the prediction and analysis capability of the model for aircraft. In view of the problem that the efficiency and quality of satellite assembly are affected due to asynchronous assembly execution and material delivery during the transformation of satellite assembly workshop from traditional single-star single-station assembly mode to multi-satellite group batch pulsating assembly mode, Zhang Lianchao et al. [54] proposed a material on-time distribution method based on Grey Theory and multi-model interaction mechanism applicable to digital twin workshop of satellite assembly, effectively solving the problem of uncontrollable path planning time under mixed environment. Aiming at the future development of space launch site, Cai Hongwei et al. [55] designed the system architecture design of digital twin of space launch site on the basis of smart space launch site construction, analyzed in detail the technical difficulties in realizing digital twin in space launch site from the realization level, and concluded that digital twin of space launch site will completely change the operation management mode, equipment support mode, task flow, organization and command of launch site, and its military application prospect is very broad. Meng Songhe et al. [56] established the frame of digital twin companion flight system of space vehicle, which is used to monitor and predict the behavior status of the space station and spaceship, reduce the transportation cost of the space station, solve the problem of missed inspection that may occur during regular inspection of spacecraft in accordance with engineering experience, improve the utilization efficiency of the spacecraft and reduce the maintenance cost.

With the help of digital twin, engineers can collect the use information of products in the real world, which is helpful for the comprehensive understanding and control of products. By collecting users' reaction and behavior data on products, they can provide reference for future improvement and innovation of products. The digital twin is applied to the storage and maintenance of solid rocket motor. The structure analysis and damage prediction of the motor are carried out with the help of real-time monitoring data, which avoids the consequences caused by erroneous judgment based on engineering experience, and simultaneously improves the precision and reliability of life prediction.

IV. CHARACTERISTIC CHARACTERIZATION AND KEY TECHNOLOGY OF DIGITAL TWIN IN SOLID ROCKET MOTOR

4.1 Characterization of Digital Twin in Solid Rocket Motor

In order to better conform to the solid motor entity and reflect the state of the motor entity more truthfully, the application of digital twin in solid motor, especially in the storage and maintenance of the motor, shall have the following characteristics:

4.1.1 Physical entity

The physical entity is the research object of digital twin, which can be the real existence that can be seen and felt in the real world, such as nozzle, combustion chamber, grain, etc., or it can also be the system and process in software form, such as thrust control system, the process of explosive grain burning surface retrogression and so on.

4.1.2 Virtual model

A virtual model is a simulation model established for a physical entity or a part of a physical entity in order to accomplish a certain function. There may be several virtual models in one digital twin. Each virtual model has a specific purpose. These virtual models that realize different functions cooperate and polymerize with each other to achieve the whole life cycle management of the physical entity. For example, the shell model shows the stress and deformation of the shell during the storage and operation of the motor, and the retrogression model shows the combustion process of the grain after ignition.

4.1.3 Physical environment

The physical environment refers to the space where the solid motor is located in the real world. The digital twin needs to measure the parameters (including temperature, humidity, salt fog, etc.) in the physical environment and input them into the virtual twin environment to make the virtual environment consistent with the physical environment, so that the simulation, optimization and decision-making for the motor entity will be more reliable.

4.1.4 Virtual environment

A virtual environment exists in a digital space, and each parameter of the physical environment is obtained by receiving sensor data in the physical environment, so as to mirror the physical environment. The similarity between virtual and physical environments is closely related to the location, number of sensors deployed and the degree of impact of their measurements on physical entities.

4.1.5 Physical-to-virtual connection

Physical-to-virtual connection is to map the state of physical entity into virtual environment, and reflect the current state of physical entity by updating parameters of virtual model, which needs to be realized by sensors, network services and other technologies in accordance with actual requirements. The system captures the state of the physical entity, compares the state data with the virtual model, determines the increment between them, and updates the virtual model accordingly.

The physical-to-virtual connection is continuous, which is a difference between the digital twin and the traditional simulation analysis. Simulation analysis is usually performed off-line based on pre-set parameters, while the virtual-real connection of the digital twin allows monitoring of state changes that respond both to the conditions of the physical environment and to make corresponding state changes in accordance with the interventions of the digital twin themselves. For example, in solid rocket motor, the deformation of current grain can be obtained by stress-strain sensor, the twin model calculates corresponding adjustment scheme in accordance with the characteristics of grain and current state, and the motor entity is controlled to execute corresponding actions through the rotation control system of motor inversion, so as to eliminate or partially recover the deformation of grain and prolong the service life of motor.

4.1.6 Virtual to physical connection

The physical-to-virtual connection is mainly data flow, while the virtual-to-physical connection mainly corresponds to the information flow and the operation process that control reality with deficiency, that is to say, the virtual-to-physical connection enables the digital twin to have the function of changing the state of the physical entity. The virtual model simulates the physical entity through the physical entity state data transmitted by the physical-to-virtual connection in accordance with its predetermined rules, thereby obtaining a set of optimal parameter values of the physical entity and the environment, and determining the difference between these parameter values and the existing states of the physical entity and the environment, thereby updating the physical entity to the optimal state accordingly.

4.1.7 Fidelity

Fidelity reflects the number, accuracy and similarity of parameters transferred between physical entity and virtual model, physical environment and virtual environment. To achieve sufficient fidelity between the virtual model and the physical entity, enough data input is required for more accurate simulation output. High fidelity requires three-dimensional physical field simulation for physical entity, which means that enough resources are needed, including data resources, network resources, computing resources, etc., which contradicts with efficiency. After all, the simulation results exceed the time limit and lose the significance of simulation. Therefore, fidelity should not be pursued as high as possible, but should seek a balance between fidelity and efficiency in accordance with specific functional requirements.

4.2 Key Technology of Digital Twin for Solid Rocket Motor

The core idea of digital twin is to update the twin model by real-time monitoring the state data of physical entity, gradually eliminate the uncertainty factors in twin model, make virtual entity and physical entity tend to be consistent, so that the state of physical entity can be reflected more accurately, and the state and operation and maintenance of physical entity can be optimized. Therefore, the realization of storage maintenance of solid motor based on digital twin needs to rely on the following key technologies, as shown in Fig 2.

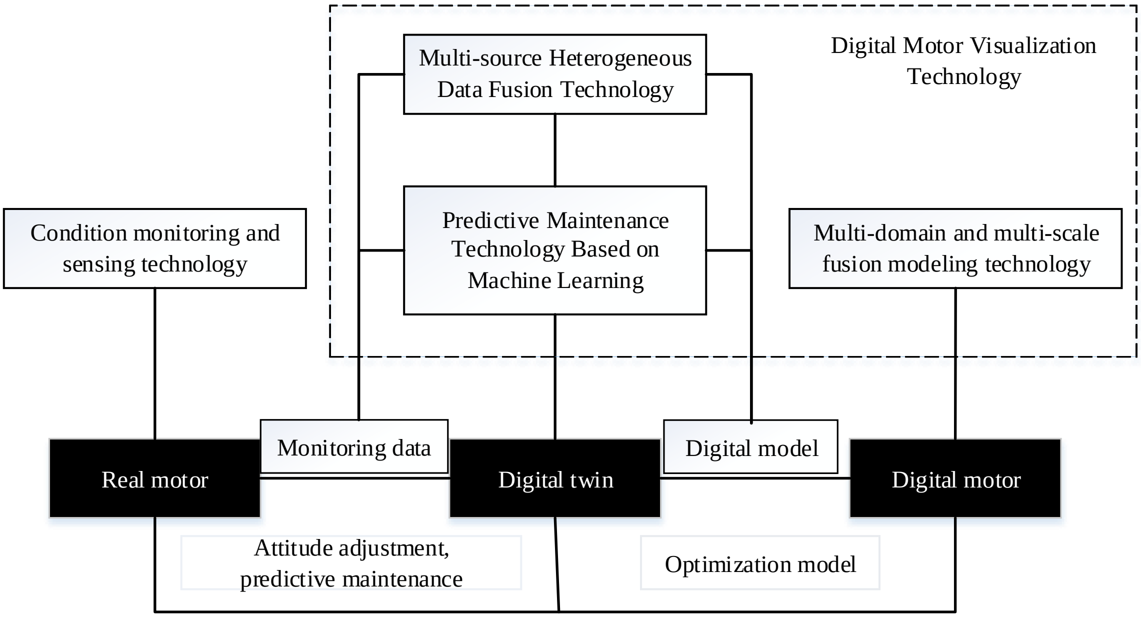

Fig 2: Key Technologies of Solid Motor Storage and Maintenance Based on Digital Twin

4.2.1 Multi-domain and multi-scale fusion modeling technology

Modeling is a process of representing physical entity digitally. In this process, physical entity in the real world need to be transformed into digital models that can be recognized by computers. The high fidelity digital model is the premise of digital twin. The purpose of modeling is to simplify the physical entity in accordance with the characteristics of the physical entity and people's understanding of the physical entity, so as to realize the reservation function. The modeling process of solid motor is influenced by many factors such as motor material properties (including physical and chemical properties), environment and load history etc. Meanwhile, the motor will experience different physical fields such as force, heat, electricity and their interactions during storage, transportation and operation. The accuracy of prediction results will be affected by the bad handling of each link. Moreover, some macroscopic representations of materials need to be better represented and reflected from the microscopic view. Therefore, the digital twin modeling of solid motor needs to comprehensively consider the effects and mutual influence of multi-domain, multi-scale and multi-physical fields, so that the twin model can more accurately reflect the physical characteristics of the motor.

4.2.2 Monitoring and sensing technology

The advantage of digital twin is that the real-time state data of physical entity can be obtained, and the digital twin model can be updated in real time with the environmental monitoring data, and the future state of physical entity can be predicted accurately. Therefore, data is the driving force for the smooth operation of digital twin, and the acquisition of original data can’t be separated from monitoring technology and sensing technology. The solid motor digital twin system obtains the structure change, stress condition, operation process and other information of the motor entity through the sensors deployed on the surface and embedded inside of the motor entity, and obtains the environmental data such as temperature and humidity through the sensors deployed in the physical environment, and makes use of these data to carry on the omni-directional state monitoring of the motor. At the same time, based on the virtual model, the future state of the motor entity can be predicted effectively by means of data mining, machine learning and other technologies.

4.2.3 Multi-source heterogeneous data fusion technology

Data is the core driving force of digital twin, and the data in digital twin of solid motor include attribute data of motor entity, operation data of control system, monitoring data of sensor (such as temperature and humidity of environment where motor is located, salt mist and so on, stress condition of motor shell, creep and aging of grain during long-term storage, damage and debonding of charge interface of motor etc.) etc. In addition, the simulation data of twin model is also an important data source, which is an effective supplement to physical data and historical data. The data in the digital twin includes all stages data of the whole life cycle of the motor design, manufacture, production, operation and scrapping etc. The data sources are different, and the data structure and data format among the data are various. To get the association relation among them, it is necessary to effectively fuse the data of these multiple sources and structures, find the law, mine the hidden information in the data, and provide data support for the assistant decision-making.

4.2.4 Predictive maintenance technology based on machine learning

Predictive maintenance is based on the acquired real-time status data of equipment to judge the current state of the equipment, predict the future status of the equipment, analyze the possible failure forms, carry out corresponding predictive maintenance in advance, remove the hidden danger before the equipment failure, so as to avoid the loss caused by the equipment failure. Predictive maintenance is an important function of digital twin of solid motor. In order to achieve better prediction results, it is necessary to collect as many data information as possible, including state data, environment data, simulation data, historical data, etc. It is impossible to process these data manually and the efficiency is too low. It can only be analyzed by machine learning. Data information is divided in accordance with corresponding knowledge structure, effective data is identified, invalid information is eliminated, correlation relation between data is mined, hidden information behind data is found, fault pattern recognition is carried out in accordance with trained machine learning algorithm to improve the accuracy of prediction results.

4.2.5 Visualization technology

The purpose of digital twin is not only to create a virtual model for the physical entity, but also to let the user understand the operation of the physical entity more intuitively and vividly through the bidirectional interaction between the virtual and the real. The solid motor can be used in the weapon equipment. Through the data visualization technology, the appearance structure of the weapon equipment can be seen, the attitude change of the weapon equipment can be displayed in real time, and the scene simulation of the battlefield environment can be realized, which can provide auxiliary function for analyzing the battlefield situation and making the battle plan. As the medium of man-machine interaction, visualization technology is the key technology of digital twin application.

V. APPLICATION OF DIGITAL TWIN IN SRM STORAGE MAINTENANCE AND LIFE PREDICTION

With the development and popularization of the new generation of information technology [57] , especially the strategy of Industry 4.0 [58-64] , Industrial Internet [65-68] and Made in China 2025 [69-70], intelligentization has attracted more and more attention and become an important direction of development in various fields. As an important power system of missile weapon, the intelligentization of solid motor is also the main theme of future development. At present, on the premise of not damaging the motor, the internal charge and bonding interface are still black box for researchers, and there are many factors affecting the performance change of the motor charge and bonding interface. Therefore, the research on the combination of digital twin and solid motor has a wide application prospect.

For the application of digital twin in solid motor, a series of fundamental researches have been carried out by domestic and foreign scholars. In order to realize the intelligent transformation of solid motor design pattern, Xiao Fei et al. [71] defined the digital twin of solid motor from three perspectives of process, model and data, established the five-layer architecture model of the overall design system of solid motor driven by digital twin, and offered preliminary implementation scheme, which provided theoretical reference for the next landing application. The related research mainly focuses on motor design, and the application of digital twin in solid motor storage has not been reported in published literature.

In view of the shortcomings in the current storage maintenance and life prediction of solid motor, this paper proposes to construct the SRM digital twin frame structure oriented to life management as shown in Fig 3, which is used to monitor the current state of SRM, update the twin model in accordance with the state data, accurately predict the storage life of SRM, and adjust the SRM accordingly in accordance with the twin model calculation results to prolong the storage life of SRM. The framework is divided into three parts: motor entity, digital motor and motor control system, in which motor entity is responsible for monitoring the change of grain, shell and environment through sensors, and transmitting data to digital motor; digital motor imports data into digital model for simulation calculation and dynamic updating to generate evaluation and decision result; motor control system converts decision result into control command for attitude control and predictive maintenance of motor entity.

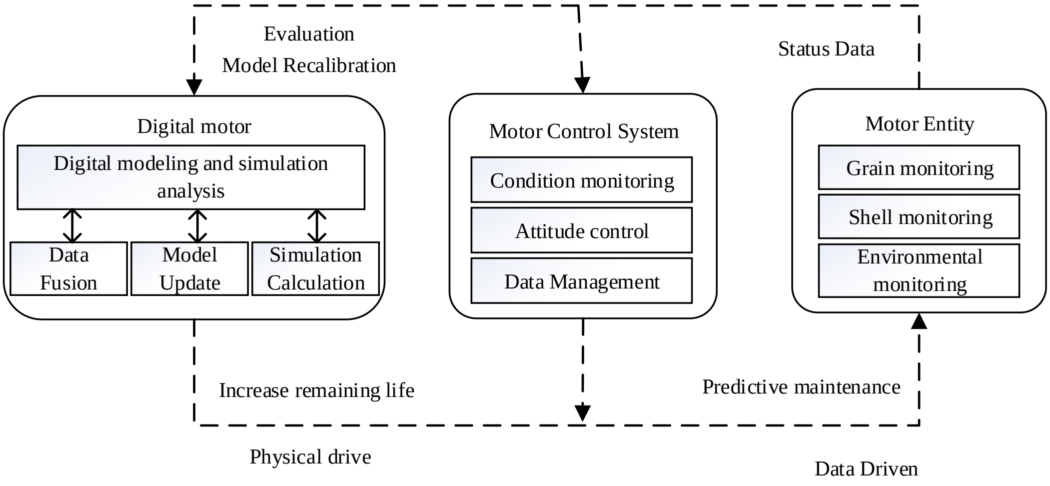

Fig 3: SRM Digital Twin Frame Structure

Data is the core driving force for normal operation of digital twin, and the process of SRM data flow in digital twin is shown in Fig 4. Firstly, in accordance with the geometry size of SRM and the attribute data of each component, the digital twin model of twin shell and grain of SRM with high fidelity is constructed with the help of multi-physical field modeling and multi-system simulation. The digital model is trained and modified based on supervised learning algorithm by using SRM historical running data and off-line data to improve the precision of the model. A variety of sensors are arranged on the surface of the motor shell and inside the charge. It is used to collect the force and deformation data, interface debonding data and propellant aging data of the motor shell and charge; collect the defect data, interface crack and propagation data of solid propellant by infrared detection and CT scanning; collect the temperature, humidity, atmospheric pressure and other data of the physical environment where the motor is located through the environmental sensor. The monitoring data enters the data processing module through the data main line for data cleaning and noise reduction. The monitoring data are standardized in accordance with uniform data format and coding rules, and the processed data are stored in SRM database as online data to lay a foundation for subsequent data analysis. The processed monitoring data are put into the corresponding simulation model of SRM digital twin body for data analysis, the abnormal data information is detected by clustering algorithm, the association relationship between the data is mined, the hidden information behind the data is found, the existing fault information and failure mode of SRM knowledge base are combined to judge whether there is a fault, and the known fault location and category are analyzed by pattern recognition method; for the unknown fault information, the machine learning method is used to classify the fault, and the Bayesian network is used to deduce the fault information to obtain the evolution process, compare the increment of the fault information with the twin model data, so as to drive the SRM digital model to update the state. The updated twin model analyzes the creep effect, the aging of the grain and the stress condition of SRM in accordance with the machine learning results, evaluates the current state of the SRM entity, predicts the remaining life of the SRM entity, calculates the decision suggestions for recovering or eliminating the motor damage in combination with the attribute data and historical running data of the motor, and transmits them to the motor control system through the data main line. The control system generates commands in accordance with the decision suggestions and drives the motor state to update, so as to prolong the storage life of the motor.

In the above process, machine learning is the core content, and the quality of machine learning results determines the accuracy of predictive results. The working process of machine learning motor is divided into model training process and deployment application process. In the model training stage, several evaluation functions should be constructed in accordance with different motor materials and historical data, the evaluation function is run with training data, the result of the function is verified in accordance with the verification data, the quality of the evaluation function is set in accordance with the verification result, and the weight of the evaluated function is increased in the next calculation, so as to guide the algorithm to approach the correct result gradually. In the deployment application stage, the model with excellent training result is deployed and applied to the prediction analysis of SRM twin model. The real-time prediction analysis is conducted through the real-time data provided by the SRM entity. The prediction result is fed back to the SRM entity. The SRM entity receives the aggregated data of the twin model, optimizes itself based on the decision suggestions given by the model, and feeds back the optimized state data to the twin model. The twin model continuously updates the predictive analysis model in accordance with the feedback result. The whole process goes round and round, which makes the prediction algorithm continuously optimized, so that the system can have a real-time insight into the running state and trend of SRM.

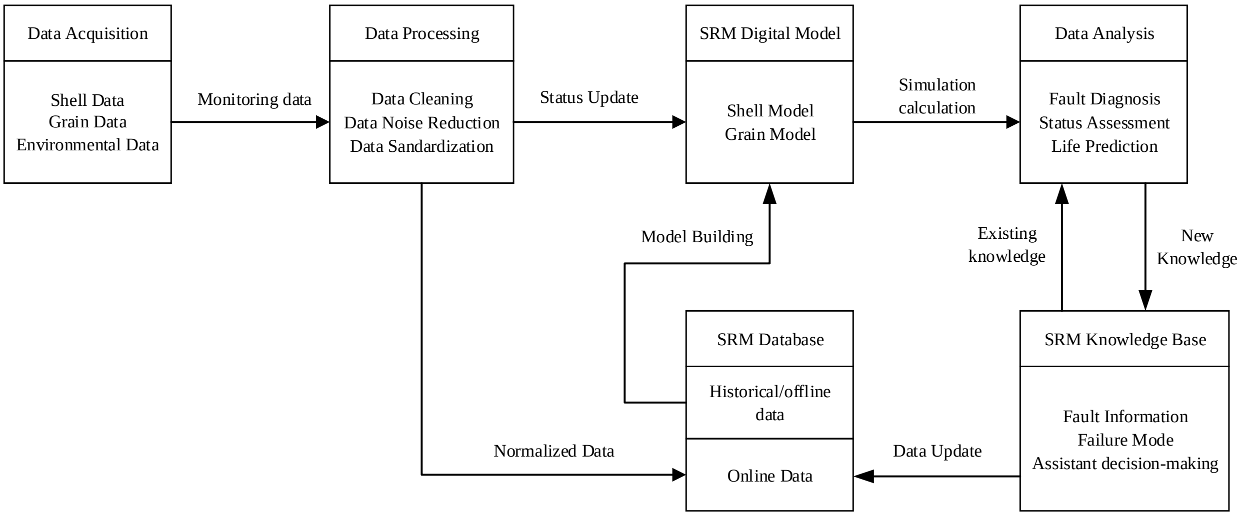

Fig 4: Data Flow in SRM Digital Twin

In the application of digital twin in the operation and maintenance of solid rocket motor, the digital twin model should not be established only from the beginning of operation and maintenance, but the most ideal thing is to establish the digital twin model of SRM from the beginning of design and production. Firstly, the design of SRM is optimized by simulation of twin model, and then the twin model is improved in accordance with the real-time data in production and manufacturing process. Only in this way can the digital twin model of SRM reflect the SRM entity more truthfully, so that the operation and maintenance can be more reliable.

VI. SUMMARY

Digital twin, as a bridge connecting the virtual and real world, can construct a high fidelity twin model for solid rocket motor, which includes all its knowledge through information fusion of multi-source heterogeneous data such as real-time state data of motor, test data and historical data of each constituent material, the twin model is driven to be updated dynamically, so as to enhance the cognition of internal change mechanism during the storage process of solid motor, to realize accurate prediction of future state of motor, so as to improve the reliability and prolong the service life of the motor. At the same time, the digital twin integrates the whole life cycle data of solid rocket motor into a unified database, which provides data support for the design of subsequent motor and greatly shortens the R&D cycle of the new motor.

At present, the application of digital twin in solid motor is still in exploration stage, and the following problems need to be further explored and discussed in the process of research and application.

(1) The state measurement of solid motor charge requires embedded sensor embedded in solid propellant during pouring, which requires embedded sensor to bear the influence of high temperature pouring and solidification cooling of solid propellant on its accuracy.

(2) The mechanism of material properties of each component of solid motor should be further explored. Only when the understanding of the material is clear enough, the model can be constructed accurately enough, and the prediction result can be accurate.

(3) The comprehensive application of digital twin on solid motor needs the data of the whole life cycle of the motor as support, and requires the coordination of production unit, user unit, testing unit and other departments, so as to realize data sharing on the premise of meeting the requirement of confidentiality work.

In accordance with the characteristics and rules of solid motor storage and maintenance, the author thinks that the following research should be carried out emphatically in the future to lay a solid foundation for the application of digital twin technology in solid motor storage and maintenance.

5.1 Modeling of Solid Motor State Prototype under Storage Condition.

In accordance with the material attribute data, the geometric models of motor shell, grain and bonding interface are constructed. Based on the experimental data, the virtual models of initial storage state, initial debonding state and initial crack state of the motor are constructed respectively. Based on the real-time monitoring data, the creep law, crack propagation law, bond interface debonding development law and particle dewetting rule of solid propellant under dead weight, overturning and rotating state are studied by using machine learning algorithm.

5.2 Measurement of Physical Response of Solid Motor under Storage Condition.

By comprehensively utilizing strain gauge, infrared thermometer, micro-CT, endoscope, laser sensor, flexible large strain sensor, fiber grating sensor and other detection methods, a three-layer Internet of Things (IOT) monitoring system is designed and constructed, which includes expandable acquisition layer, data preprocessing layer and application support layer. Data format of different equipment is analyzed and unified data standardization processing is carried out. Random forest algorithm is used to effectively fuse multi-source heterogeneous data, and the model is updated and iterated in real time and timing in accordance with the data source, so as to continuously improve model accuracy.

5.3 The Inversion of Solid Motor State Parameters under Finite Sample Constraints.

Based on Hooke-Jeeves algorithm, the parameters of interface cohesion model were inversed to determine the optimized interface parameters. For particle dehumidification, the stress-strain curve was obtained by simulation calculation, and then compared with the experimental curve, the optimization objective function of particle dehumidification damage parameters was established, and the particle dehumidifying damage parameters were identified by iteration step by step; the creep parameter determination method of solid propellant based on deep learning was established, and the creep parameters of solid propellant were back determined based on creep experimental data; the back propagation (BP) neural network algorithm was used to invert the propellant damage parameters in combination with numerical simulation and experimental data.

5.4 Study on Storage Performance Prediction Method of Solid Motor Driven by State Update.

Based on the contribution of different sensors to the storage performance of solid motor, the multi-sensor data are fused in accordance with D-S evidence theory. The fusion information represents the current state of the specific functions of solid motor. The state information drives the virtual model updating iteration, and the updated model is used to predict the storage performance of solid rocket motor based on migration learning and filtering algorithm.

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