mathematics

Review

Review of the Digital Twin Technology Applications for Electrical Equipment Lifecycle Management

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Abstract: Digital twin is one of the emerging technologies for the digital transformation of the power industry. Many existing studies claim that the widespread application of digital twins will shift the industry to a principally new level of development. This article provides an extensive overview of the industrial application experience of digital twin technologies for solving the problems of modern power systems with a particular focus on the task of high-voltage power equipment lifecycle management. The latter task contours one of the most promising areas for the application of the digital twins in the power industry since it requires deep analysis of the technological processes dynamics and the development of physical, mathematical and computer models that cover all the potential benefits of the digital twin technology. At the moment, there is a lack of reliable data on the problems of assessing and predicting the technical state of high-voltage power equipment. The use of digital twin technology in modern power systems will allow for aggregating data from a variety of real objects and will allow the automatization of collecting and processing of big data by implementing artificial intelligence methods, which will ultimately make it possible to manage the life cycle of the power equipment. The article puts to scrutiny the industrial experience of digital twins creation, considering the technical solutions suggested by the largest manufacturers of electrical equipment. A classification of digital twins, examples and main features of their application in the power industry, including the problem of managing the life cycle of high-voltage electrical equipment, are considered and discussed.

Keywords: digital twin technology; digital twin applications; smart energy; equipment lifecycle management; electrical equipment

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1. Introduction

1.1. Digital Twin Technology

The concept of the digital twin was first introduced by Michael Greaves [1]. Today, this term can be given a specific definition. The digital twin is the real projection of all components in the product life cycle using physical data, virtual data and data in between [2]. The digital twin includes data on the characteristics of the object in a detailed mathematical model, the parameters of which are refined using the actual data.

Along with the term digital twin, another term has emerged—the digital shadow. A digital shadow is a system of links and dependencies that describes the behavior of a real object, usually under normal operating conditions, reflected in redundant big data obtained from a real object using industrial Internet technologies. With the use of a digital shadow, it is possible to predict the behavior of a real object, but only under the conditions described by the collected data. However, it does not allow the modeling of a situation in which the real object was not operated.

In [1], digital twins are divided into three types:

- Prototype of the digital twin, which contains data sets that can be used to build a physical version of the object (Figure 1). The prototype includes object requirements, specifications, etc.;
- Instance describes a specific physical object linked with the digital twin associated with the object throughout the entire lifecycle. The instance includes a 3D model, data from measuring instruments and sensors, and testing results (Figure 2);
- The aggregate is a combination of digital twin instances. It receives data from many physical objects (Figure 3).

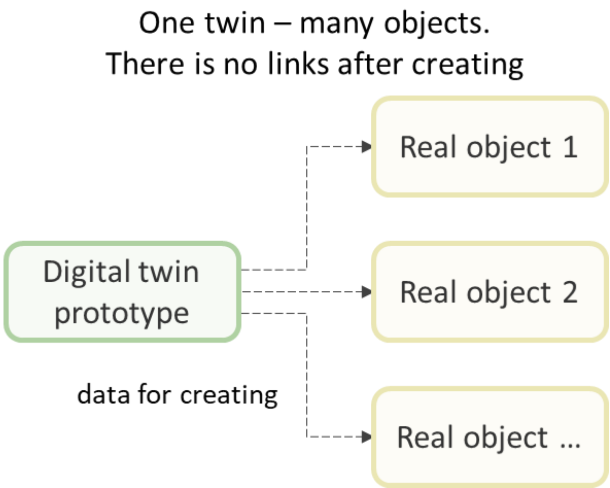

Figure 1. Digital twin prototype.

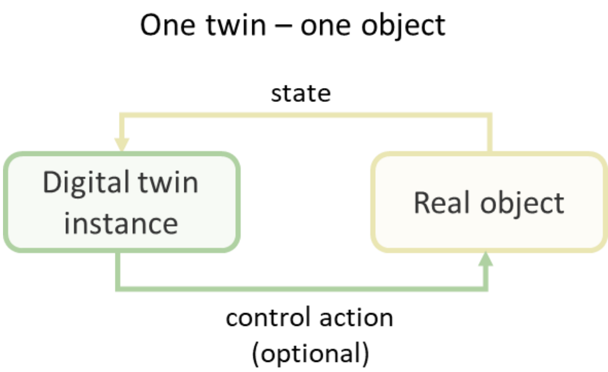

Figure 2. Digital twin instance.

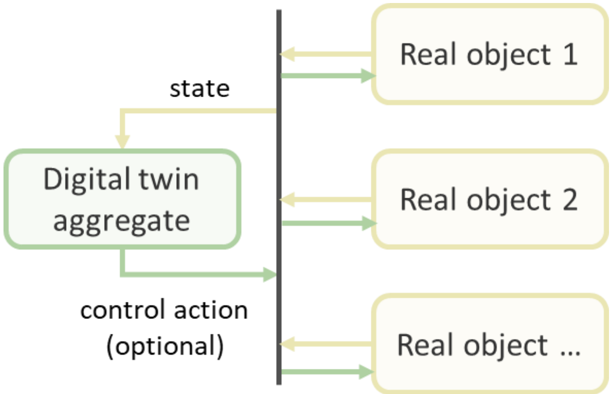

Figure 3. Digital twin aggregate.

The development of digital twin technology has led to the specification of their types [2]: digital twin of the product, process digital twin, and digital twin of the system.

Today, digital twin technology is actively used in the fuel and energy sector to solve various technical and technological problems. The digital twin makes it possible to detect deviating parameters in the operation of industrial equipment with extremely high sensitivity—even if they do not yet affect the state of the equipment and, therefore, are not recorded by traditional control and monitoring systems.

1.2. Digital Twin Studies in the Power Industry

Most of the research in the field of digital twins in the power industry is focused on the following issues: assessment of the power equipment technical state [3–8], control of the power system operation modes [9,10], optimization of energy consumption [11] as well addressing the technical issues of renewable energy sources integration [12].

The article [13] presents a study on digital twins of electrical networks using an ontological approach. In accordance with the proposed approach, the digital twin technology is used to study the power system operation modes and ensure its security. When building an ontology, the following levels of system description were addressed [13]:

- Top-level (research, modeling, functioning of the objects of a specific subject area);
- Subject level (formulation, alignment and classification of the problem-oriented concepts).

The implementation of the project using the ontological approach includes the development of the object prototypes, testing the prototypes of digital twins and establishing information interaction of simulated and measured data flows.

In [14], scenarios for using a digital twin technology for the Cai-Lun substation (China) are presented. The main provisions laid in the design of the digital twin are:

- Simulation of the system in real and quasi-real-time;
- Ensuring data transfer between the ontology-based system and the digital twin.

This method is based on the connection of various types of knowledge in the digital space. The digital twin for the analysis of the simulated system takes into account the uncertainty of the system caused by the presence of various consumers, generators and the probability of power equipment failure. The Cai-Lun substation model is based on real-time monitoring data of various systems, a three-dimensional model of the substation equipment and a decision core.

In [15], a method for real-time assessment of the distribution network reliability based on digital twin technology is presented. The method uses technical data, information from external systems, and monitoring systems' data on the current state of the power equipment. At the same time, it uses the presentation of the power equipment on holographic maps. Implementation of the digital twin concept using holographic evaluation allows the method to:

- Improve the assessment of the power supply reliability of the distribution network;
- Increase the accuracy of the network reliability prediction by providing real-time simulation of the topology changes;
- Improve the network reliability by adjusting its configuration, load reduction at weak power distribution zones, and provide network development recommendations.

Due to the increasing requirements for the environmental performance of the power systems, many countries are implementing projects to support decision-making on the construction of power plants based on renewable energy sources (RES). Due to the complexity of their operation, digital twins are being introduced to facilitate their design and operation processes.

In [16], a study of the application of the digital twin concept using 3D modeling technologies for the implementation of an intelligent system to support the operation and maintenance of a photovoltaic power plant is presented. In [17], digital twin technology is applied to predict the generation of tidal power plants.

1.3. Industrial Cases

The relevance of using digital twin technology in the energy sector is confirmed by the projects of many large industrial and technological corporations.

Siemens Corporation has developed a digital twin SiprotecDigitalTwin of the Siprotec 5 digital protection device [18]. By creating a digital twin, the utility operating costs were reduced due to the considerable reduction of the power equipment emergency downtime. The cloud application introduced by Siemens contributes to a significant reduction of short circuits (SC) elimination time when searching and eliminating failures.

A comprehensive solution that allows the development of digital twins, presented by Siemens Corporation, is MindSphere [19]. This solution has the functionality for working with the power system equipment, a wide range of open MindSphere APIs, including analytical services, and a MindSphere Store with ready-to-use applications.

In order to create a complex cross-industry solution, ABB implemented the ABB Ability product [20]. As a part of the ABB Ability, an Aspect Object technology was implemented, which means it is possible to create a digital twin of real equipment.

General Electric develops and implements digital twin technology based on the PREDIX platform [21]. The PREDIX platform has found wide application in the creation of the gas turbines' digital twin. The platform includes a digital turbine model, intelligent database, and analytical unit, which determines the current state of the turbine and predicts its performance.

IBM has realized and implemented a system for creating digital twins named IBM Engineering Lifecycle Optimization [22], aimed at assessing the actual technical state of the equipment.

The American company Paladin Gateway has developed and implemented the Power Analytics platform [23], which consists of various services with the possibility of hosting them in the cloud, allowing for the creation of digital twins, software management tools and exchange power system monitoring data.

Rotek JSC has developed the Prana diagnostic system [24] for assessing the technical state of steam turbines, generators, transformers, boilers, pumps and gas piston units.

The core of the Prana system is a multidimensional state model of the equipment—a digital twin which analyzes how the equipment works within the control period and in real-time mode. The system uses the technologies of neural networks and big data.

The VNIIAES company developed the software and hardware solution named Virtual Digital Nuclear Power Plant (NPP) with Water-Water Energetic Reactor (WWER) [25]. The system is based on a digital twin of a nuclear power plant. It applies complex calculations of a variety of processes at nuclear power plants: from the neutronic, thermal and hydrodynamic characteristics of reactors to the cumulative economic effect acquired when using various systems and materials. In such a model, it is possible to calculate the behavior of new equipment before it is installed at real power units, assess its compatibility and impact on other systems, and simulate equipment failures, external influences and incorrect actions of the engineering personnel.

The company Productive Technological Systems has developed and implemented a digital twin of the turbine with the axial exhaust Kr-77-6.8. The digital twin was implemented on the basis of Creo [26] and Windchill [27] software. The use of a digital twin made it possible to reduce the turbine manufacturing time from 2.5 years to eight months.

In Russia, in 2018, a decree was issued [28], which led to the occurrence of the Digital Transformation 2030 concept at PJSC Russian Grids [29], the completion of which should be the transition to the new generation of digital power networks.

In order to achieve this goal, the digital twin concept is being introduced, representing the creation of an integration platform for a wide variety of existing operational and information technologies and data processing systems. As a result of combining the technologies, the digital twin platform makes it possible to synchronize heterogeneous data so that a digital model corresponds to the physical one.

In [30], the development of the concept of a digital twin using 3D modeling technology to build the Smart Grid in 23 districts of Tokyo (Japan) is presented. The Plateau project represents a three-dimensional urban space that simulates urban life and existing and expected loads of the power transmission system. The project is aimed at planning electric power network development and operation, urban planning, disaster prevention, and improving the quality of life of Tokyo residents. The major advantage of the project is the possibility of its application by various city services.

As can be seen, the use of digital twins in the power industry is a vast topic. This review focuses on the features of using digital twins for power equipment lifecycle management, technologies and data necessary to implement the concept of a digital twin. At the same time, the article also covers examples from adjacent areas when describing the technologies necessary for the creation and proper operation of digital twins. The review also focuses on the analysis of the existing methods and technologies for designing the digital twins, creating the mathematical models of electrical equipment for power engineering facilities and describing the input data.

The article is structured as follows. The second section provides an overview of the problem of power equipment lifecycle management in modern power systems and shows the fundamental differences between simulation modeling and digital twin modeling. The third section contains an overview of the methods and technologies for implementing digital twins. The fourth section describes the data and technologies for data storage and processing, which is of crucial importance for creating and implementing digital twins. Discussion and generalization of the presented materials are provided in the conclusion.

2. The Difference between Simulation and Digital Twin Concept for Power Equipment Lifecycle Management

2.1. High-Voltage Equipment Lifecycle Management

The modern electric power system is a complex technical system, the development of which is aimed at the introduction of renewable generation, distributed generation, electric power storage facilities, the development of Smart Grids and ultra-high voltage power transmission technologies. These innovations cause a sharply variable nature of power production and consumption, which increases the load on high-voltage equipment. It emphasizes the need for increased monitoring of the technical state of power generation facilities, transmission and distribution networks, and electrical installations of the consumers. Moreover, frequent failures of the power system elements result from the low controllability and observability of the power systems facilities.

In order to extend the life of the equipment and maintain its operable condition at all stages of the life cycle, energy utilities are implementing various systems for monitoring and diagnosing the power equipment state [31].

In accordance with [32], the life cycle of a system is understood as a set of processes that describe the state of the system from the stage of formulating technical requirements to the stage of its decommissioning.

Each system of any structure and purpose is typically considered in the context of the time of its application. When designing and operating the system, such models are built that reflect the changing properties of the object under study. Simulation models are created for this purpose called life cycle models. The life cycle model is segmented into several stages because it makes it easier to plan, prepare, and operate the system. Segmentation depends on the imposed requirements corresponding to the period of the system application and the decision-making mechanisms aimed at reducing the risk of the system operation [33].

Stages (or phases) of the life cycle make up a structure within which the processes of the system under study are described by certain models. The beginning and the ending of each stage represent decision points. Each stage has its own tasks, and the transition from one stage to another is an unequivocal event. The order, sequence, and duration of the life cycle stages and their number are unique for each system. The life cycle processes (system, software, service) can be launched simultaneously, iteratively, and recursively, depending on the stage in focus [33]. Table 1 lists the standard stages of the power equipment life cycle.

Table 1. Power equipment life cycle stages.

Stage	Description
Engineering survey	Stating basic requirements and regulations for the formation of design documentation
Design project technical assignment	Detailed elaboration of the requirements, creation of technical specifications
System design	Construction planning and designing, patent search, coordination of system and equipment requirements
Construction and installation	Installation and testing of the designed installations and systems
Commissioning	Design project inspection, as-built documentation, adjustment and testing of the installations
Pilot operation	Approbation of the system, carrying out tests confirming the system's operability in accordance with the technical specifications and project documentation, putting the system into operation
Equipment operation, maintenance and repair	Operation of equipment according to the instructions and standards, ensuring stable, reliable and secure operation of the system
Decommissioning	Archiving and disposal

The life cycle is a complex indicator of the period of existence of the system under consideration. At each stage of the life cycle and during the transition from one state of the system to another, based on the current technical state and regulatory documentation, decisions are made to change the parameters of the system and extend or reduce each stage of the life cycle. The described process is called lifecycle management. Life cycle management is complicated by the influence of various external factors (economy, market signals, policy, climate, etc.) and factors that describe the system or the object (operation experience and the complexity of technological processes, etc.).

In [33], the following principles related to the life cycle model are defined:

- During the life cycle, the system goes through certain unified stages;
- The duration of each stage varies depending on several internal and external factors and can be changed by different control actions;
- The transition from one stage to another is described by a qualitative change in the parameters of the system, depending on the expert ranking of the criteria reflecting the fulfillment of the tasks of each stage;
- The criteria for the transition from one stage to another are based on risk reduction goals and depend not only on regulatory documents but also on the retrospective data of operating a particular system.

There are various methods for assessing the effective duration of each stage of the life cycle. The methodology of transition between the stages is based on the assessment of the physical wear and obsolescence of the assets in focus. Obsolescence of the first kind is characterized by a considerable reduction of equipment manufacturing costs due to the appearance of analogs with better properties and characteristics. Obsolescence of the second kind is interpreted in different ways. The methodology for choosing economically viable terms can be based on the following:

- A comparison of reduced costs for aged and new equipment.
- Assessment of the duration and structure of the repair cycle using information from technical diagnostics and relevant information systems.

2.2. Simulation of the Equipment Lifecycle Management

In order to increase the efficiency of the design stage, the simulation method is used. The method consists of replacing the designed system with a model, where the experiments are carried out to obtain information about its operation under various control actions and environmental conditions [34]. The simulation model is a dynamic model, where processes are considered only at the increasing time scale [35].

The main goals of the simulation are [35]:

- Description of the behavior of the system;
- Construction of the hypothesis;
- Prediction of the system behavior;
- Reproduction of the system's functioning process in time with the preservation of the elementary physical phenomena and their structure in order to obtain information about the state of the system in the future.

Modeling involves simulating the operation process of an object in order to highlight the problems and find ways to ensure the reliable operation of the equipment under various requirements and conditions. The input parameters, in this case, include the parameters of the technical state associated with the operational process of the equipment, the probabilities of occurrence of various conditions, the duration of the certain state, and failure probability. Monitoring allows us to assess the technical state of the equipment or process in real time, allowing us to adjust measures for its maintenance and repair.

The simulation also gives the opportunity to solve the following problems:

- Uncertain and contradictory information;
- Multicriteria problem statement of the power equipment design;
- Impossibility of precise goal formulation;
- The presence of implicit restrictions and the relationship between them;
- The dynamic change of the external conditions;
- Minimization of the equipment defects arising from the design stage errors;
- Determining the conditions for the system development;

When comparing simulation with other mathematical approaches, the following specific features can be distinguished:

- Iterative process (to refine the system state assessment);
- Use of statistical modeling methods;
- Pre-processing of information in order to clarify the input data;
- Use of various simulation methods.

Various methods of mathematical analysis are developed and applied to determine and predict the technical state of the power system facility and plan and adjust the power equipment maintenance and repair (MR) schedules [36]. Today, systems are being developed based on big data using machine learning algorithms. In this case, the output is an estimate of the current technical state of the equipment or predictive values of the state's major parameters [37]. However, the application of these methods does not allow for making decisions on optimizing the operation of the power equipment depending on the external conditions and requirements without the participation of the expert. The concept of the digital twin makes it possible to take into account all the above-described shortcomings of the classic simulation approach.

2.3. Digital Twins Technologies for Power Equipment Lifecycle Management

The concept of digital twins can be effectively used to coordinate all stages of the life cycle of the power equipment through the accumulation of retrospective data from various sources and data on the current technical state. The digital twin can be used as a single source of data about the power equipment unit, which is used to implement decision support for its further operation. This concept allows modeling, monitoring, diagnosing and control of the technical state of the controlled object [38].

At the operational stage, by using digital twin technology, it is possible to implement real-time dynamic monitoring of any process or equipment unit. The application of the digital twin concept for continuous technical state monitoring contributes to the localization of faults, prevention of emergency events, and quality control of the technological process or a specific power equipment unit [38].

While standard mathematical models are based on the solution of algebraic differential equations, the calculation of partial derivatives, historical data and expert estimates, the digital twin technology also includes monitoring and diagnostic data on the current state of the system to build the model.

Unlike the simulation models, the digital twin, due to the presence of the feedback link between the physical object and the model, allows self-adjustment when the state of the system changes. After processing the data at the information level and transferring it to the application level, the model is recalculated. Then recommendations are generated for optimizing the system operation and managing the power equipment life cycle. For example, article [39] presents an approach for diagnosing fuel cell failures using a digital twin. The digital twin is built on the basis of a thermodynamic model with real-time sensor data updates. Fault diagnostics are carried out by calculating and estimating the residual vector. If the residual vector crosses the fault detection threshold, the fault is localized using a sensitive residual.

When using a digital twin, it becomes possible to assess and manage the technical state of a particular power equipment unit throughout the entire life cycle. In contrast, during the simulation, only optimization of the design stage is possible.

In this case, a mathematical model is needed not only to understand how an object or process works. It also describes the structure, properties, and laws of interaction with the surrounding world in order to learn how to control an object or process as well as to determine the best ways to control it. Moreover, the most important thing for digital twins technology is to predict the consequences of impacts on an object or process. Thus, it is possible to assess and manage the technical state of a particular node of power equipment throughout the entire life cycle.

Thus, digital twin allows you to use the current data from the object of study, retrospective data from single (in the case of the digital twin instance) or multiple (in the case of digital twin aggregation) objects, provides physical and mathematical modeling with the opportunity of the power equipment life cycle prediction, as shown in Figure 4.

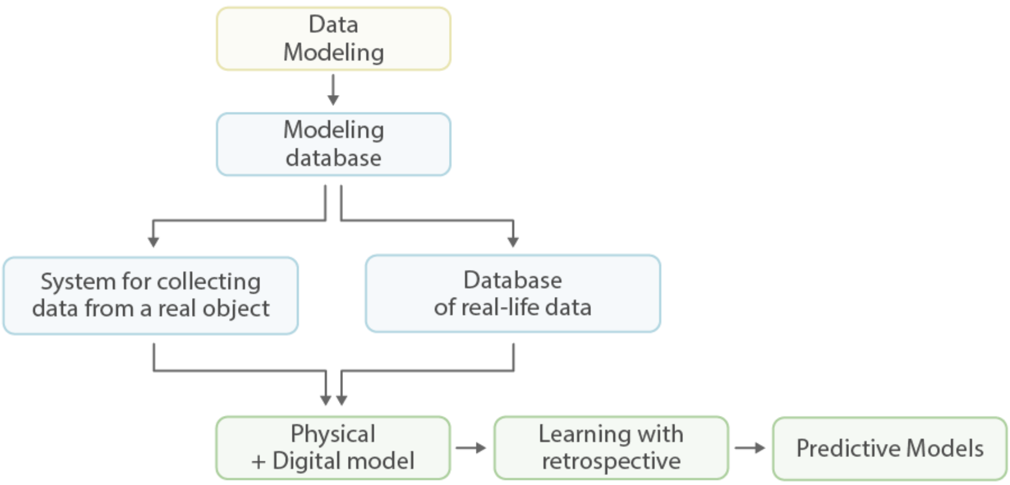

Figure 4. The main elements of the digital twin model for power equipment life cycle management.

The digital twin technology helps to coordinate all stages of the life cycle of the equipment or process under study since not only statistical, regulatory and retrospective data are taken into account, but also current state monitoring and diagnostic data.

From the foregoing, the application of the digital twin technology can be of great value for solving the problems of managing the technical state of the power equipment serving as a data-driven intelligent software tool able to:

- Propose solutions for updating and building up the MR plans;
- Provide recommendations on the choice of the MR strategy:
  - scheduled preventive maintenance;
  - condition-monitored maintenance;
- Implement equipment data management for various business processes;
- Simulate development, production, and implementation of the equipment;
- Reduce the risks of introducing innovative solutions;
- Analyze and predict the technical state of the equipment at any stage of its life cycle.

Usually, the development of the power system facility includes the following four stages: design, transfer of the project to the production phase, manufacturing and testing of a prototype, and finally, starting commercial production. In the traditional paradigm, the majority of the design project updates occur throughout the development phase. Moreover, the number of design project updates and the associated costs increase dramatically from the design phase to the commercial production.

When using a digital twin, due to the opportunity to take into account the requirements from various development stages, to model external and internal processes, and to synchronize various sources of information, it becomes possible to concentrate necessary changes and updates, shift and minimize the costs at the design stage. Moreover, it makes sense to use such a digital twin in the subsequent stages of the life cycle.

In [40], an example of applying the digital twin concept using virtual and augmented realities is presented. Virtual reality, with the help of 3D simulation, allows operators to be immersed in a digital twin environment. Augmented reality technology helps to transfer virtual information to the physical environment. Thus, developers are able to test the objects on virtual simulators, reducing assembly costs and time for conducting real experiments at the development and design stages. These digital twin technologies can also be applied at other stages of the life cycle for the engineering staff to be immersed into the digital twin environment to analyze the operation modes of the equipment under study and reveal the potential defects at early development phases.

In fact, maintenance and repair activities may be referred to as a tool for managing the life cycle of the power equipment. Currently, there is a worldwide transition from scheduled preventive maintenance to condition-based maintenance. The scheduling of preventive maintenance is based on the standards and regulations with no regard to the actual technical state of the equipment. Condition-based service is based not only on the standards reflected in the technical documentation but also on the current technical state of a particular item and the results of its technical diagnostics. This approach improves the efficiency of resource planning at the enterprise.

The digital twin technology contributes to the implementation of condition-based maintenance, as it provides the opportunity to analyze the actual technical state of the power equipment under study and make relevant recommendations based on the results of predictive analysis. At the same time, due to the application of different technologies that find implicit links between data from different sources, the accuracy of determining the actual state increases [41]. In [42], the implementation of the state-of-the-art maintenance of the wind turbines, based on the digital twins' technology, is presented. In [43], the authors present the application of digital twins for choosing the optimal maintenance and repair strategy of a power converter. Depending on the operating conditions of a particular item, a different maintenance and repair strategy can be chosen, which is carried out by means of digital twin technology implementation.

Notable among that is the connection between the technology of digital twins and the development of cyber-physical robotic systems for the tasks of monitoring and assessing the state of electrical equipment. Moreover, as shown in [44], digital twin technologies can be used both to form optimal routes for unmanned diagnostic systems and to design power system facilities that would be initially more suitable for the use of cyber-physical robotic systems.

2.4. Drawback of Digital Twins

The disadvantages of the digital twin include the following:

1. The high complexity and cost of creating a software part. Firstly, this includes the development of mathematical models and the involvement of an interdisciplinary team of specialists (engineers, IT specialists, system analysts, data science specialists, and information security specialists). Secondly, there is the high complexity of implementing a computer model with sufficient accuracy and high detailing of processes.
2. The need to use hardware, hardware-software, and telecommunication systems for collecting, transmitting, and storing large amounts of data with protection against loss and data integrity violations. For many existing utilities of the power industry, creating a digital twin would require very large investments in digitalization just to realize the collection and transmission of the necessary data in real-time or near real-time.
3. Cyber threats: the digital twin as a decision support tool or automatic control of industrial, energy, and logistics facilities is vulnerable to attackers. They can inflict critical damage by distorting the output actions of the digital center and disrupting the technological process. For example, the integration of software and physical high-voltage equipment of a power station and substation creates a threat of damage to electrical equipment by introducing malicious code into the software part of the system. The failure of electrical equipment can lead to a cascade effect: from a power plant/substation shutdown to a blackout within the region. This, in turn, can lead to mass accidents and man-made disasters in transport systems, enterprises, and in life-support systems. At the same time, the aggregate-type digital twin is connected to many physically existing objects at once, which creates the risk of a massive catastrophic attack.

   Since the digital twin is a complex hardware and software system, often distributed, many vulnerabilities arise. These include vulnerabilities in data transmission channels, the ability to connect to data collection elements, database vulnerabilities, and the ability to penetrate the supervisory control system. In the case of using machine learning for decision-making, it is necessary to take into account the vulnerabilities associated with data poisoning, as well as the substitution of machine learning models and the threats associated with the low interpretability of machine learning models: in other words, the risks of unpredictable critical errors. Building reliable protection and cybersecurity of the digital twin will require very large investments and continuous monitoring to identify vulnerabilities, threats and attacks.
4. The economic effect of the introduction of digital data manifests slowly since aggregation of a large amount of data is required. Another feature is increasing the accuracy of decision-making, for example, in the task of managing the life cycle of electric grid equipment. It gives a deferred economic effect, which manifests itself in an increase in the life cycle and a decrease in accidents. There is a risk that the expected effect will not be achieved due to the use of incorrect models, an insufficiently high level of observability of the object's elements, or errors in the program code. At the same time, as shown above, the costs of developing, implementing, and maintaining digital twins are very high. As a result, the payback period is too long, often longer than the decision-making horizon in companies.

3. Using Digital Twins for a Large-Scale Power System Facility

3.1. Levels of Digital Twins Architecture

One of the first steps in creating a digital twin is creating a data model that reflects the geometry, attributes, behavior and principles of operation of a physical object. The architecture of digital twins consists of the levels [45] presented in Table 2.

Table 2. Digital Twin Architecture.

Level	Description
Physical level	A set of attributes of an existing object: geometric parameters, physical properties, rules for changing the state of the object, and functional requirements (including the interaction with other elements of the system in which the object is operated).
Model level	Projection of the attributes and characteristics of the physical level into a virtual space.
Information level	Implementation of the interaction between the physical level, the model level and the databases, libraries of the models, and knowledge base.
Application level	Analysis of the processes, control actions, decision-making algorithms, and knowledge. Formulation of the proposals for managing the life cycle of the real object.

From the physical level to the level of the model, information about the parameters of the system arrives, thus, refining and expanding the mathematical models. From the level of the model to the physical level, control actions and proposals for optimizing the operation of the equipment are received [45]. In general, the information level is used to solve the following tasks [46]:

- Verification of the coincidence of the assumptions about the existing systems and models with real data acquired from the online monitoring systems;
- Building up the information sets processed at the application level;
- Presentation of the ontologies and standards.

The integration of the information model into the digital twin system is implemented by the introduction of interface modules that connect the model with the following elements: power system design supporting tools based on CAD systems and gateways for collecting data from sensors and sending commands to actuators, developed on the basis of the Industrial Internet of Things (IoT).

It is shown in [47] that the development of the concept of digital twins can contribute to a change in the development paradigm based on cloud technologies, 3D modeling technologies, and IoT.

Cloud technologies and edge computing have found application at the information level since this level requires the implementation of real-time synchronization functions between the physical level and the model level, between the databases, as well as with the application level.

The application level is necessary for such tasks as generating decision-supporting recommendations, performing predictive analysis about the changes associated with the object of study for a specified time span, and identifying new strategic options for developing a system to obtain economic effects.

At the application level, such technologies are used that process vast of heterogeneous data coming from a physical object and store it at the information level, solve optimization problems and provide decision support [40,46]. The algorithms and methods used at the application level may be classified into the following two groups:

- Traditional/deep machine learning algorithms;
- Supervised/unsupervised/reinforcement learning.

Artificial intelligence and machine learning algorithms can be used to detect anomalies and equipment defects, find the cause of an anomaly or the location of a defect, and protect the communication channel between the physical and the information levels of the digital twin [40,48,49].

In order to connect different levels and subsystems of the digital twin, IoT technology is used, which aggregates and pre-processes data from heterogeneous data sources [7].

The digital twin should implement the following functions [7,40]:

- Data management (managing calculation assumptions, evaluation of the calculation results, taking into account the uncertainty of the system);
- Closed-loop feedback (adaptive model update and optimization);
- Interaction between the model and the physical object in real-time (increasing awareness of the current parameters of the system);
- Integration of digital technologies, supporting system engineering, and creation of the multilevel matrix of indicators for the various stages of the life cycle.

3.2. Approaches and Tools for Digital Twins' Development

Table 3 shows some of the approaches and tools used for digital twins' modeling when dealing with the specific tasks of the energy sector.

Table 3. Approaches and tools for digital twins' modeling.

No	Model Name	Application	Approaches and Tools
1	Digital twin of the servo scanning system	Predicting the state of a physical model	Blender, Python
2	Digital twin of the power equipment (power transformers, switches, power transmission lines, etc.)	Optimization of the equipment operation modes and predictive analytics of the power equipment technical state	3D modeling Neural networks Artificial intelligence
3	Digital model of the photovoltaic power plant	Solving the problem of predicting the generation of electrical energy by the photovoltaic modules	DBT systems (data conversion) Python Machine learning algorithms
4	Motion performance control of machine tools, manipulators	Monitoring and control of the kinematics of complex mechanical systems	Matlab Python
5	Digital model of the company's staff behavior	Control and forecasting of the staff behavior	Deep machine learning
6	Digital twin of the solid fuel engine	Solving the problem of measuring data from solid-state engines	AstroLab
7	Digital twin for evaluating the development process	Shortening the development cycle, accelerating the execution of business processes	MPD-Processor
8	Digital model for coal mining enterprises	Implementation of automatic coal mining	Theory
9	Digital model of the workshop production system	Producing 3D visualization and monitoring of the workspace in real time	3D-monitoring Petri net
10	Industrial park "production-operation-storage"	Improving the accuracy of decision-making; implementation of adaptable and interactive management and system control	MatLab
11	Multidimensional scalable smart manufacturing space	Implementation of multidimensional integration of physical, information and business space	Plant Simulation
12	Cloud platform for intelligent material and technical planning	Solving the problem of intelligent planning of material and technical resources	Theory IoT
13	Power system models	Processing information from the power system subject to the existing constraints	Multivariate analysis tools Big data IoT

In [40,46,49], the main provisions for the development and application of the power system facilities' digital twins are given. The main issues to be focused on when developing the description of the object are the following:

- Choice of ontologies, concepts and relationships, which are the basis of the information model;
- Tracking the impact of various components and limitations on the system at all stages of the equipment life cycle;
- Refinement and modification of the model;
- Selection and implementation of methods for combining the ontologies of several objects (for complex power systems and their facilities).

3.3. Industrial Examples

The Nrjpack software package, built on the command query request segregation (CQRS) architecture, implements the automatic downloading of a set of information about an object that can be used for ontological modeling. Nrjpack is an effective solution for finding the optimal configuration of a hybrid power supply system containing power generation equipment, including renewable energy facilities, storage devices, consumers and power distribution facilities [46].

With increased requirements for the calculation speed (for nuclear reaction processes at a nuclear power plant, emergency operation modes), the task of finding the optimal solution with reduced calculation time and space for storing the information can also be solved by evolutionary algorithms, as well as HRES optimizers, simplified models of a reduced order [45,46].

The methods used to reduce the order of the mathematical problem under study may be divided into the following [45]:

- Simplification method (criteria for early termination of the calculation process, coarse-grid approach, reduction of the degree of freedom of the system, division of the big task into several ones);
- Projection method (internal orthogonal decomposition, reduced basis method, Krylov subspace method, balanced truncation);
- Fitting method (polynomial regression, Gaussian process regression, support vector regression, neural networks).

Checking the operation of the selected configuration can be implemented by using the models of MATLAB Simulink or models created using deep neural networks. Data from the power equipment monitoring systems and actual consumption from the metering devices are received through IoT gateways.

Spirit implements 5G network technology when creating a digital twin [40] of the communication system between a crawler vehicle or unmanned aerial vehicles and a start/launch point, intelligent systems at industrial enterprises.

The application of the 5G system for a smart factory, for example, has reduced the failure rate of electrical equipment by 70% and reduced the cost of maintenance and repairs by 25%.

The paper [50] presents the application of ensemble machine learning algorithms in building the concept of a digital twin to optimize the operation of a petrochemical plant in the energy sector.

In [51], a digital twin of a photovoltaic panel of a solar power plant is described using a hybrid neural network, which is used to simulate the current-voltage curve of the photovoltaic system depending on environmental parameters: irradiation, temperature and humidity. The link between the physical model and the digital twin was implemented by using IoT technology.

In [4], the study on the application of a digital twin to predict the power generation of a wave power plant is presented. In the project, with the help of artificial intelligence algorithms, wave height is predicted in real-time in order to provide timely energy generation calculations. Data collection is also carried out using intelligent sensors of the IoT system.

In [41], a review from General Electric is presented on the application of the digital twins of the power plant equipment (steam turbine, gas turbine plant, boilers and compressors). The digital twin implementation at the power plant in [41] is based on the following types of models:

- **Physical Models**
    - Thermodynamic model:
        - prediction of the power equipment operation in quasi-stationary and transient operation modes;
        - modeling of the gas turbines, steam turbines, and boilers; modeling of the heat balance in the GateCycle application.
    - Anomaly detection models and methods:
        - modeling the state of the technical equipment using time series and remote monitoring data;
        - detection of the developing defects and providing decision support on their impact on the power equipment under study.
    - Life cycle model:
        - aggregating the data on the operation modes, site-specific information, and outages from the whole power equipment fleet;
        - simulation and analysis of power equipment operation scenarios in order to implement condition-based maintenance and repair strategies.
    - Dynamic evaluation and tuning of the model in transient processes:
        - matching thermodynamic performance model with the measured sensor data from the power plant;
        - implementation of the model consistency analysis, assessing the applicability of the existing model to the current operating conditions.
    - Dynamic flow and combustion models:
        - optimization of the compressor and turbine sections of the power plant at the design stage;
        - analysis of the turbine operation modes from the point of view of the flow and thermal physics of the real object model.
- **Artificial intelligence models and methods**
    - Pattern recognition:
        - application of artificial intelligence methods for behavioral analysis and refinement of physical models.
    - Model training:
        - continuous creation, verification, tracking and updating of the models due to the permanent link of the digital twin with the physical object.
    - Unstructured data analytics:
        - interpretation and analysis of unstructured enterprise data, which make up approximately 80% of the total amount of available data;
        - semi-automation of the tasks of setting up models, analytics, and analysis of the model quality using various error metrics.
    - Multimodal data analytics:
        - predicting failures and maintaining automatic, operational and up-to-date estimates of the power equipment state.
    - Knowledge networks:
        - connecting experts, providing common access to the sensors and high-precision metering devices to assess the current state of the equipment.

Siemens has established a partnership with DecisionLab Ltd. to develop the Agent-based Turbine Operations & Maintenance (ATOM) product for the state monitoring and maintenance activities of aviation gas turbines. The major problem in carrying out maintenance and repairs of aviation gas turbines was the participation of other organizations. Therefore, when analyzing the technical state of turbines, it was necessary to take into account the production processes that could not be described by the available databases [52]. The ATOM system uses big data technologies and machine learning algorithms to analyze heterogeneous data. A distinctive feature of the system is the possibility of dividing the model into several modules and analyzing each part of the gas turbine power plant separately in order to provide a deep analysis of the system state and highlight the major influencing factors.

In [53], a digital twin of an onshore wind turbine was developed, which monitors the effect of turbulence and wind speed on power converters. The digital twin is implemented on the basis of the physical turbine model that reflects the electrodynamic and thermal processes. Based on the Metropolis–Hastings random walk algorithm and discrete wavelet transformation, the wind speed and turbulence parameters are reconstructed based on the averaged data with 1 s resolution over a 10-min interval. Based on these data and data from temperature sensors, the graphs of the conductor materials' fatigue are built. When comparing the fatigue value calculated by the digital twin and the value calculated by using stochastic methods using the average, maximum and minimum wind speeds from Supervisory Control and Data Acquisition (SCADA) system, it turned out that the actual fatigue was four orders of magnitude higher than the value calculated based on the averaged parameters acquired from the SCADA system. Another example of the digital twin technology application for wind turbines is presented in [54]. In this paper, digital twins are used to analyze the reliability of wind turbines.

In [55], the authors describe the application of a digital twin to correct the values obtained from wind speed sensors at wind farms. The Virtual Wind Sensing Digital Twin extends the platform of physical sensors using virtual ones. The behavior of the sensors is simulated using a spatiotemporal wind model, taking into account the correlations between the measurements obtained from different sections of the wind farm. After determining the wind conditions, the model estimates the accuracy of the physical sensors. When a deviation is detected, the selector identifies faulty physical sensors and replaces their measurements with the estimated ones. The statistical error of the proposed method is 0.45 ± 0.009 m/s, and the sensitivity is 1.083, from which it can be concluded that the digital twin technology can be used to estimate the wind speed and verify the wind speed values.

In [56], a digital twin of a wind turbine is suggested for solving the problems of monitoring the technical state of the wind turbine and predicting energy production. The digital twin of the wind farm uses a new generation 5G radio access network and cloud technologies. Predictive modeling is implemented using deep learning, temporal superfine regression and non-parametric k-nearest neighbor regression. The forecasting procedure consists of two stages: processing data from a single-dimensional time series of wind speed and estimating energy production.

In [57], the authors suggest the digital twin of a wind turbine using the SCADA data for predictive analysis of the turbine behavior and scheduling of the maintenance and repair. The digital twin, implemented in MATLAB Simulink and MATLAB Sunscape, corresponds to a 1500 MW wind farm with a fleet of wind turbines with hydraulic drives and mechanical brakes capable of reducing or stopping axis movement at wind speeds ranging from 4 m/s to 25 m/s.

4. What Data Is Needed to Create a Digital Twin and How to Work with It

Data is the basis of digital twin technology since the efficiency of the models embedded in the digital twin depends on the data quality and quantity. In order to arrange the exchange and analysis of the digital twin data, the following items should be properly addressed:

- Data sets sufficient to implement data analytics;
- Systems for collecting and processing data acquired from the physical objects and SCADA systems;
- Database technologies: database management systems (DBMS): Oracle, MS SQL, DB2; open-source DBMS (PostgreSQL); cloud storage (S3, RedShift, Greenlum); distributed file systems;
- Elements that implement service provision and human-machine interface (HMI) interaction;
- Provision of communication between the elements of the system.

In addition, the architecture requires the storage of the models based on machine learning, which may also include a knowledge base. An example of a system that includes a real object, a database, a SCADA system, subsystems for assessing the technical state and an AI-based decision-support module is shown in Figure 5.

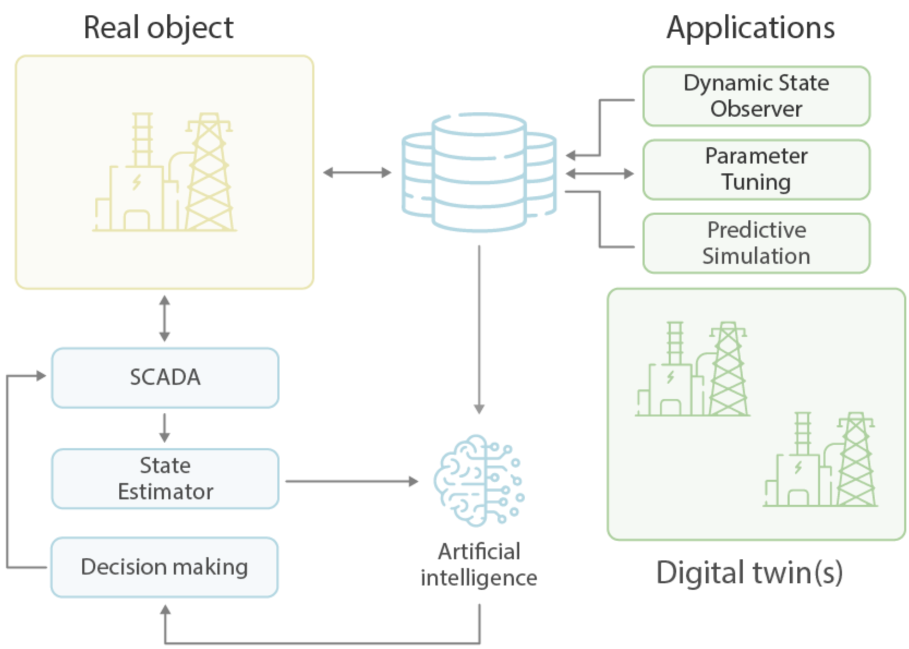

Figure 5. Digital twin architecture for the real object control system.

The data set depends on the type of the digital twin and the tasks for which it was created. In order to build a digital twin of the electrical network, it is necessary to have [15,46,57]:

- The database of the network's digital twin;
- Technical information: relay protection and automation settings; current-carrying capacity of the conductors; list of the power equipment with the corresponding characteristics and parameters; estimates of the power equipment damage and defects; residual service life of each power equipment unit, etc.;
- External data: data on power equipment maintenance and repairs, strategic development plans; asset management strategy and plans; data from the geographic information systems and maps, weather data, and energy consumption data.

In [14], the digital twin of the Cai-Lun substation was implemented based on the following:

- Data collected from monitoring and diagnostic systems;
- Power network intelligent systems using neural networks, deep learning methods, and statistical analysis to provide decision support in operation and control;
- Cloud computing solutions for establishing an interconnection between the information system and the physical object.

4.1. Input Data

The ATOM system for assessing the technical state and managing maintenance and repairs for Siemens gas turbines uses the data on the turbines' operation history and their technical parameters [52].

In [41], the authors present the results of the study of the General Electric company dedicated to the digital twin technology implementation for gas turbines, boilers and compressors. The initial data for the correct operation of the system is the following:

- **External conditions' data:** *Ambient temperature, air humidity, load, weather forecast models, and market prices.*
- **Equipment technical data:** *Measurements from the monitoring systems, parameters of the fuel mixture, mechanical, static and dynamic loads on the equipment, and electrical parameters.*

To build a digital twin of wind turbines, data, such as [27,53,54] rated passport parameters of the turbines, current and historical operation parameters and meteorological data are required.

In [58], the study on the development of the substation automatic walker system is presented. The information stored in the digital twin databases of the substation equipment and automatic crawler system includes the following parameters: the object; object type; equipment position (longitude and latitude); rated voltage; rated power; operating time; manufacturer. The crawler creates a data packet and transmits it through the wireless interface of the general radio service node to the gateway support node at the link logic control level. Next, the gateway decompresses the data and converts them into the formats available for transmission over the network.

In [59], a study on the implementation of a digital twin for nuclear power plant equipment is presented. The digital twin includes a nuclear power plant simulator and machine learning algorithms for predictive analysis. In order to justify the implementation of complex information systems at the critical infrastructural facility, the study was initially conducted. The data for the digital twin in this study was obtained not from real objects but from a simulator. The data sets included time stamps, temperature, water level and flow rate, steam flow rate, reactor coolant flow, steam generator pressure, containment level, enthalpy, nuclear reaction parameters, and total thermal power of the reactor.

In [60], a study is presented on the application of the concept of digital twins for high-voltage power transmission lines using IoT technologies and methods of holographic perception of the power cables. IoT systems are used to aggregate data from various sources and increase the speed of synchronization between a real object and a digital twin [60,61]. The technology is implemented using intelligent sensors, RFID tags, and intelligent information storage devices.

The study [37] describes the implementation of the digital twin instances of 110 kV voltage and current measurement transformers in order to solve the technical state estimation problem. A system of sensors and physical, mathematical and 3D spatial models were developed for this project.

A monitoring system has been developed as a set of sensors and a diagnostic system based on essentially different methods of non-defective diagnostics. A 3D model of the equipment under study is also referred to as an integral part of the digital twin concept. The advantages of the digital twin technology application were highlighted as well.

In the study [15], in order to obtain the basic information about the parameters of the 10 kV, 35 kV distribution network and 110 kV power network equipment, it is suggested to use the PMS 2.0 system through an interface program. By using the PMS 2.0 system, it is possible to obtain information on the state of switching equipment (power switches, disconnectors, fuses, circuit breakers), the state of the power transmission lines (connected/disconnected), and the supply centers (power transformers of different voltage classes).

Geographic data, which is imported as a topological grid, is used to reflect the actual location of the equipment and the structural relationship between the power equipment units. Maps are used to analyze the data routes and reliability metrics.

When adding the information about the network (topology, switching state, equipment and loading parameters) to the model, the map reflects the reliability characteristics in accordance with the following colors [15]:

- Green—high fault tolerance;
- Blue—good fault tolerance;
- Yellow—transformers and substations;
- Orange—low-reliability indicators, network overload in normal mode;
- Red—low fault tolerance, the network is on the verge of failure.

In the study [62], a digital twin based on the IoT Framework was designed by dividing the development process into two parts: in the first, the information exchange is established between the model and the physical object; in the second, data preprocessing using cloud technologies is organized. The information exchange is treated as a separate critical task in order to minimize the communication delays between the object of study and the cloud and to ensure the raw data confidentiality and integrity. At the same time, machine learning technology is implemented on smart sensors for local pre-training of aggregated data models, thereby reducing delays and avoiding the transfer of raw data. In [63], the application of the blockchain system was proposed to improve the security of the aggregated data storage system.

4.2. Technologies of Data Storage and Processing

In order to ensure the effective processing of heterogeneous data, a proper database is to be arranged. In [58], the use of Oracle relational databases, which possess the properties of atomicity, data consistency, and durability, is presented to solve the problem of optimizing the application of the power equipment monitoring systems. The Oracle database system implements the functions of storing, processing, and updating the data. Through the interface integrated into the data transmission platform, the predefined parameters (active, reactive power, power factor, voltage levels) enter the Oracle database system.

In [46], relational databases are used to process events that change the structure of the information model and its content. Relational database systems, in this case, allow for the creation of relational projections of various levels of complexity.

For pre-processing of the information, boundary calculations are used. Cloud technologies are used to work with big data, provide synchronization between the different levels and subsystems of the digital twin, as well as to perform complex data analytics. MTConnect protocol and knowledge resource centers are used to manage data [64].

In order to analyze data coming from sensors and information systems, it is necessary to introduce the corresponding elements and modules of data analysis. General Electric uses the following products [41]:

- Predix (analysis of sensor data, data management and data analysis on the operation of production assets, information security);
- Predix-Machine (providing secure bi-directional connection and asset management; providing information to the applications, cloud storage, and internet connection via the OPCUA, and Modbus protocols);
- Advanced controls and peripheral computing (supervisory control).

4.3. Industrial Case Studies

In [65], a study on the implementation of the digital twin for building an enterprise network architecture is described. Nowadays, grid companies face problems resulting from incompatibility standards for managing the electrical network, the need to integrate new monitoring and diagnostic systems, adopt new technologies, and the need for the transition from the scheduled repair strategy to condition-based maintenance.

In order to build a digital twin of an enterprise, it is necessary to design and implement digital twins for all the equipment units, business processes, technologies, and security systems. The general digital circuit of the digital twin, built on the basis of the State Grid cloud platform and the ECS server [65], consists of the following:

- The physical level, integrated with the unified control systems (SG-ISC), digital tools for monitoring and managing the power grid projects;
- The data storage level is in the form of a relational SQL database system (storage of the object's architecture, data about the applications, technologies, and security systems) and a cache database (Redis) implemented for data visualization;
- The service level, consisting of the search engine, visualization, analysis and service applications;
- The functional level implements data analysis and control actions, which solves the tasks of changing the architecture of the object, displaying the infrastructure, maintaining architecture analysis statistics, generating maintenance and repair plans using the Vue architecture visualization frameworks and intelligent search using the EChart system.

To unify and consolidate data analysis at the application level of the digital twin, the company developed the PSS®ODMS and PTI software (Siemens, Munich, German). The software receives operational information about the system for processing and analysis. Functions are the sources and the recipients of data:

- Power flow calculations of the network (PTI PSSE/E from Siemens);
- Calculation and adoption of the relay protection settings (PTI PSSE/E from Siemens);
- Network modeling and data management (PTI ODMS from Siemens);
- Real-time data archiver (PI Historian from Siemens);
- Company project management (Primavera from Oracle, Austin, TX, USA);
- Geospatial analysis (GeoSpatial Analysis from General Electric Company, Boston, MA, USA);
- Intelligent asset management and monitoring (Maximo from IBM, Armonk, NY, USA);
- Production asset management (ESPRIT form Hexagon AB, Stockholm, Sweden);
- Business process management (SAP NetWeaver Business Process Management from SAP SE, Walldorf, Germany).

The Siemens PTI PSSE/E system receives a model of the system as an input and provides the calculation results of the power flow mode (voltage, loading conditions, power flows), analysis of the power system operation mode and its dynamics [65,66]. At the output, the system issues the necessary calculations and modifies the settings.

The Siemens PTI ODMS calculates the network mathematical model used for the adaptive protection and automation systems. The input parameters for calculating the network model are current operational data (voltages, electrical currents, power flows) and asset hierarchy.

The Maximo system visualizes backbone networks using Geographic Information System (GIS) data, SAP data, Primavera, relay protection and automation settings, as well as Siemens PTI PSSE/E and Siemens PTI ODMS calculations. When the model or network mode changes, the feedback is applied to the physical object. Changing the network model or electrical mode leads to the corresponding changes in adaptive relay protection and automation algorithms and settings.

The system ELVIS is a digital twin for the backbone electrical network developed by the Fingrid Oyj (Helsinki, Finland) solves the problems of managing assets and ensures power network interoperability, unification of data flows, and uninterrupted data exchange in real-time, reducing the costs and increasing the reliability of the system [67].

Together with the increasing speed of computing systems and the development of data transmission methods, digital twin technology is also changing. In the future, digital twin technology will allow for not only analyzing the current state of objects or processes in real time but also predicting their change. This step will make it possible to increase the reliability of the functioning of power systems by increasing their information observability.

5. Conclusions

The relevance of using the digital twin technology for the tasks of managing the life cycle of electrical equipment lies in the fact that specifically digital twins allow solving one of the main problems of this task, which is the integration of physically existing electric power facilities and intelligent information systems. In order to implement a digital twin of the instance or aggregation, a connection is required within the framework of the integrated hardware and software system of the physical objects under study, equipment for collecting, transmitting, storing and processing data, physical and mathematical models, analysis, diagnostics, forecasting and control models based on artificial intelligence algorithms. That ultimately drives the development of information technologies and the digital transformation of the power industry.

The introduction of the digital twin technology, even in the case of the implementation of only a digital shadow, will significantly speed up the collection of big data in the power industry, which is necessary to implement the next step. This step is the creation of intelligent decision-making systems. At the same time, the digital twin can organically develop along with the introduction of new technologies, starting from the equipment model, its technical passport and operation history, almost infinitely increasing its functionality by reaching the status of integrated intelligent life cycle management systems connected to a variety of real power system facilities and allowing to conduct in-depth research.

The advantage of a digital twin is the possibility of using various technologies to form optimal strategies for controlling actions on a simulated object. It also contributes to the evolutionary development of technology, as it allows enterprises in the energy sector to obtain an economic effect already at the initial stages of technology implementation.

In addition, this article compares the areas of application of digital twin technologies and simulation modeling. Simulation models are used to optimize the design phase and are based on static data using standard analytical methods, while digital twins can be used to optimize life cycle stages, analyze the transition from one stage to another, and form an optimal life cycle management strategy in order to adjust the duration of the stages. The use of digital twins is the basis for choosing maintenance and repair strategies.

Digital twins will allow the implementation and development of the online systems for monitoring and diagnosing the technical state of the power equipment, as well as online and offline decision support systems. The main requested effect of the system, in this case, is the reduction of operating costs and the opening of new ways for the development of energy utilities.

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