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Review

A Review on Digital Twins and Its Application in the Modeling of Photovoltaic Installations

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Abstract: Industry 4.0 is in continuous technological growth that benefits all sectors of industry and society in general. This article reviews the Digital Twin (DT) concept and the interest of its application in photovoltaic installations. It compares how other authors use the DT approach in photovoltaic installations to improve the efficiency of the renewable energy generated and consumed, energy prediction and the reduction of the operation and maintenance costs of the photovoltaic installation. It reviews how, by providing real-time data and analysis, DTs enable more informed decision-making in the solar energy sector. The objectives of the review are to study digital twin technology and to analyse its application and implementation in PV systems.

Keywords: Industry 4.0; digital twin (DT); review; photovoltaic installations; renewable energies

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1. Introduction

Renewable energy generated worldwide will have to increase its capacity threefold by 2030, i.e., installed renewable capacity will have to increase from 3382 GW in 2022 to 11,174 GW, in order to limit the global temperature increase to 1.5 °C above pre-industrial levels, according to the International Renewable Energy Agency (IRENA) [1]. In this scenario, solar photovoltaic (PV) and wind energy together account for 90% of the added renewable energy capacity.

In this context, today's society is undergoing some major changes due to the rapid and massive technological growth that has taken place in recent years. The advancement of Industry 4.0 and the increasing availability of data and computing power are some of the causes of this societal transformation [2]. One of the most useful tools brought about by these advances is Digital Twins, a term that has been around for several decades [2]. Using Digital Twin (DT) allows for the simulation of any process, product or system, as well as the optimisation of resources and offers the possibility to make better decisions. DT enables predictive maintenance, remote and real-time monitoring and innovation [3].

General Electric estimates that the use of Digital Twins in operations management and monitoring helps prevent annual losses of $1 billion in deployed assets [4]. The global Digital Twins industry is estimated to be worth $125.7 billion by 2030 [5].

Digital cufflinks can be used in a wide variety of fields, as can be seen in [4,6] and are as follows: industrial production, education and healthcare [4]. This widespread use can be attributed to the future need to increase the installed renewable photovoltaic capacity [1]. In this specific research, a comprehensive literature search on the current state of the art in Digital Twin methods and tools, as well as an evaluation, analysis and comparison of their use in PV systems was performed.

Research on the use of the Digital Twins in photovoltaic installations has received little attention, so, with a detailed and insightful review, this paper aims to:

(1) Study and describe the term Digital Twin, its parts and how it functions;
(2) Analyse the different applications and use of Digital Twins, summarising the significant tools that could be interesting for this study;
(3) Analyse and compare studies in which Digital Twins have been applied to photovoltaic installations. An outline of the objectives of this article can be seen in Figure 1.

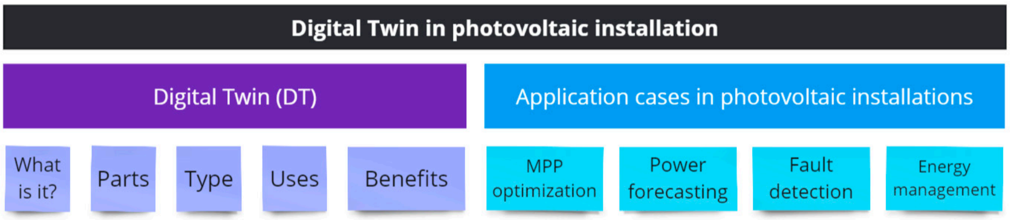

Figure 1. Outline of the objectives pursued. Source: Own elaboration.

The remainder of the paper is organised as follows: Section 2 describes the literature review methodology, Section 3 describes the Digital Twin technology and its method, Section 4 reviews the different types of Digital Twin applications that could be transferable to our case study and Section 5 evaluates the conclusions drawn from this paper.

2. Materials and Methods

2.1. Classification Criteria

The main keywords for the literature search were "digital twins for photovoltaic installations" and the main databases were Scopus, Web of Science and IEEE.

For this article, two different searches were carried out in different sources. First, we searched for articles published in the previous three years related to Digital Twins using the keywords "digital twin", in ScienceDirect, Scopus and WebOfScience. A second search was then carried out. This time using the keywords "Digital twin in photovoltaic installations" in Scopus, WebOfScience, ScienceDirect and IEEE. From the first search, the most relevant articles were selected, taking into account their introduction and abstract parts. This selection was made in order to gather the crucial information for the purpose of this work, which is to explain the general concept of Digital Twins and their main uses. The second search was carried out in order to gather as much information as possible about the application of Digital Twin technology, that is of most interest to this research, which is the implementation of this technology in a photovoltaic installation. From this second search, very few articles were found (9, specifically), so we intend to consider all of them.

2.2. Methodology

For the sake of explanation, the literature review method will be divided into three steps: collecting, filtering and sorting.

Step 1: This first step consists of collecting the literature published in the last three years, from January 2020 to June 2023. Databases such as Scopus, WebOfScience, IEEE Xplore and ScienceDirect are selected. The method of literature collection has been shown above. Search keywords are chosen and used to see if the topic and content of the article are useful for the purpose of this research.

Step 2: To filter the literature collected during step 1, some crucial parts of the articles (abstract, introduction and conclusion) are read. If these parts of the article contain information that shows relevance to any topic related to this study, such as the definition of digital twins, types and classification of twins and Digital Twins in PV installations it is kept for review, otherwise it is rejected.

Step 3: Classification of the previously reviewed literature is done by reviewing each article and summarising common claims and similarities.

3. The Digital Twin (DT)

3.1. The Digital Twin Concept

The term Digital Twin has no standard definition, although NASA's definition is the most widely accepted [6]. In 2010, NASA proposed and developed, in writing, the term Digital Twin [2]. It defines DT as a "multiphysics, multiscale, probabilistic integrated simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to reflect the life of its corresponding flying twin." [7]. In 2014, Professor Michael Grieves wrote a book in which he formally defined the main parts of a Digital Twin. These parts are the physical model in real space, the digital model in virtual space and the data connecting the two models [8].

Ref. [9] defines a virtual model as a "copy" of a physical model or real system that can mimic, characterise and describe its properties and performance from multiple temporal and spatial viewpoints. It has all kinds of data, such as material properties, geometric dimensions or historical performance data, to drive and model a simulation that can be used to control, optimise or even predict the actual performance of physical entities.

In addition, in ref. [9], the concept of a multidimensional Digital Twin is proposed. This modelling method provides a detailed description of the model composition and behaviour and introduces the TRIZ function model in a five-dimensional framework, which improves the Digital Twin construction process. In ref. [10], a Digital Twin based on biomimicry is proposed.

In ref. [11], it is debated whether the concept of a Digital Twin can be considered a technology. Following this discussion, it can be said that, depending on the context of the research, a Digital Twin can be considered as a technology, concept, system, paradigm or innovation. Furthermore, ref. [11] distinguishes a Digital Twin from current digital models and systems, as well as defines the digital shadow. For the digital model or system of a real system to be considered a Digital Twin, there has to be bi-directional data flow through the IoT between the digital model or system and the real system it represents in the digital environment [12,13] (see Figure 2).

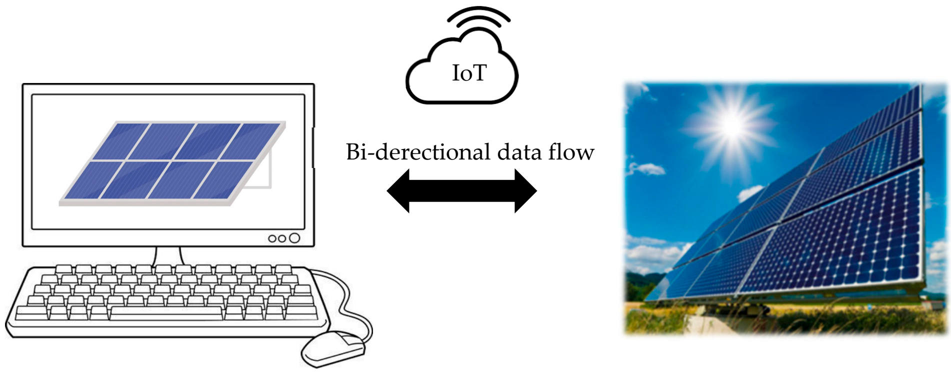

Figure 2. Schematic of a Digital Twin applied to PV installation. Source: Own elaboration based on the definitions and references given in [11].

When the data flow is only in one direction, then it is not a Digital Twin but a digital shadow [14] (see Figure 3).

The Digital Twins can be classified into three types according to [3], which are as follows:

- Digital Process Twin. The term Digital Process Twin is used when the physical model in the real environment is a manufacturing process. In this way, the DT of a process can predict the operation of the manufacturing process, thus detecting possible faults. This facilitates preventive maintenance, knowing the right time to carry it out.
- Digital Product Twin. This is a digital representation of a given product, so that manufacturers can predict the product's lifecycle and optimise the performance of their products before producing the product. This translates into cost savings.

- System Digital Twin. In this case, the characteristics of the two types seen above are encompassed. To create the DT, a large amount of data is needed on how the system works, what the system's devices produce and what the system produces in general.

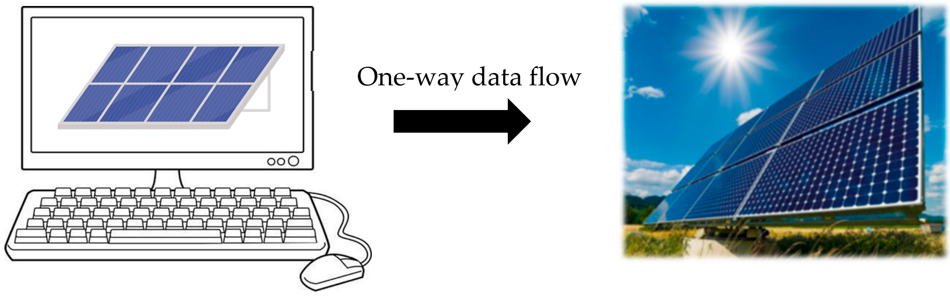

Figure 3. Schematic of a digital shadow applied to a PV installation. Source: Own elaboration based on the definitions and references given in [11].

According to the classification of ref. [3], a Digital Twin applied to a photovoltaic system will be of the Digital System Twin type.

3.2. Physical Model or Real System

This is the physical system, process, product or service for which a Digital Twin is to be obtained in order to simulate its behaviour. In order to be able to optimise resources, improve efficiency, control and monitoring, as well as to be able to make more informed operational decisions [3], such a model or system should be exchanging its state data with the Digital Twin through the IoT [12,13]. Therefore, the physical model or real system must be monitored, in the case of this article the object of study is the solar photovoltaic energy system.

3.3. Data Exchange

The exchange of data between the real and the digital environment is one of the main parts of a Digital Twin, as previously discussed [8]. The sources and categories of data are diverse and can generally be divided into physical and virtual data [15]. In 2017, cyber-physical systems were defined as "a new trend in research work related to the Internet of Things, in which physical systems act as sensors to collect information from the real world and communicate it to computational modules to corresponding physical systems through a feedback loop." [16] while in 2019 "cyber-physical systems are multidimensional and complex systems that integrate the dynamic cyber and physical worlds." [17].

The evolution of Industry 4.0 and the Internet of Things (IoT) means that through communication protocols with sensors in the real environment, data can be collected and shared from the real world with the digital world thanks to network connectivity [18–20]. In [11], a list of the different tools applied in studies using DTs is provided. Some of these tools used are, fourth and fifth generation mobile communication networks (4G and 5G), Wi-fi, LoRaWAN, ZigBee, ZWave, etc. [10]. Some of the layer protocol applications are MQTT, HTTP, XMPP, etc. [10]. In addition, some platforms mentioned in [11] are Azure Digital Twins, Predix (GE Digital), MindSphere (Siemens), etc. [21]. Other tools used are wireless sensors and Artificial Intelligence (AI).

The collection of data of the PV installation, as well as the variables that affect its operation, can be done through the PVGIS database [22] or by using different communication protocols to receive data from power meters, data analysers, pyranometers, temperature sensors, weather stations, etc. [23–27].

4. Digital Twin Applications

4.1. The Digital Twin in Agriculture

The agronomy sector is full of demanding and complex tasks. First of all, agriculture is a field where the outcome is not always related to parameters under human control: weather and climate conditions, soil quality, etc., all affect the outcome of the process in unpredictable ways. In addition, it requires continuous monitoring and management of any situation that may occur at that time: farmers must constantly assess and deal with situations such as pests, diseases, etc. All of this makes it a vital activity for human development and most people are not willing to sacrifice all of this effort for the little reward it offers.

In this sense, Digital Twins seem to be a very interesting tool to apply in agriculture. The use of this technology can help monitor, control and optimise farm management. This allows farmers to be in control from a distance without having to be present. This also allows them to take immediate action when necessary or to estimate the effects of interventions through virtual farm simulations based on real-world data [2].

The work in ref. [28] includes an implementation model based on the Internet of Things that runs in real time and is characterised by fidelity and complex intelligence. It also includes a control model based on a similar system. This model provides the possibility for farmers to control and simulate their farms remotely [28]. Another example is the application of Digital Twin technology to potato harvesting. In this field, the parameters used to program the harvesters by the operators are set, taking into account the data from the previous year's harvest and the intuition and wisdom of the worker, so the efficiency of the device depends largely on the operator's experience. In ref. [29], they proposed a Digital Twin model for the following situation: a plastic replica of a potato with the same characteristics as a real potato. Sensors were used to detect collisions and possible damage to the product, so that the system could act and avoid possible losses at harvest time. The data are studied and presented to the machine user in real time, giving the operator the opportunity to adjust parameters and increase productivity while ensuring the integrity of the potatoes [29].

4.2. Digital Twin in the Food Industry

Digital Twin technologies can be used to increase productivity and reduce waste in any industrial process, but especially in the food manufacturing industry, which could be of particular interest. The food processing field needs answers to issues such as food safety and wholesomeness, sustainability, climate change and changing consumer demands. The use of Digital Twins makes it possible to monitor, control and predict all these factors. The main aspect of food quality is freshness, which is related to the environment in which the product is located and preserved. Since food preserved at low temperatures maintains moisture and freshness better, parameters such as temperature, humidity or light appear as environmental factors that affect all of the above-mentioned characteristics and are therefore of great interest to keep under observation.

Monitoring these parameters with the help of synchronised sensors is the main source of data available to reproduce the chemical breakdown of food in a virtual environment. The biochemical degradation of molecules can be simulated because it is a known and mathematically described process.

In ref. [30], they proposed a control method for food processing plants based on Digital Twins. This project is composed of three main elements (as is any Digital Twin model, as explained earlier in this paper) which are the following: the food process operation (physical entity), a virtual replica of the food process operation (virtual model) and the IoT platform (twin data). The IoT platform provides the framework and tools necessary to integrate the communication of the sensors. The data collected by the sensors during the process are used to drive the operation of the virtual model. The synchronised, real-time operation of both processes (real and virtual) allows for the accurate control of the process and production operation [14].

4.3. Digital Twin in Photovoltaic Systems

In each of the points in this section, articles that apply Digital Twin technology to PV installations are reviewed. Applying this technology to a solar PV system will allow for the monitoring, control and management of the renewable energy generated and consumed by the PV installation [31–34], as well as fault detection by comparing the output of the DT and that of the PV system [22,34–36]. This would enable the optimisation of photovoltaic renewable energy production [37,38].

Another application of DT technology applied in PV installations is the prediction of renewable photovoltaic power generation [39,40]. One of the most outstanding aspects of the use of a Digital Twin is the possibility to make decisions in an effective way [3].

4.3.1. Optimisation of the Search for the Maximum Power Point

This section compares the use of a Digital Twin (DT) for the Maximum Power Point Tracking (MPPT) in [37,38].

The behaviour of photovoltaic cells under different conditions is characterised by their V-I curve [41]. The maximum power (P_{MPP}) that can be obtained from the PV module is at the point where the product of the voltage (V_{MPP}) and the current (I_{MPP}) is the maximum. This point varies with the irradiance conditions and the ambient temperature [42].

Maximum Power Point Search (MPP)

Since the MPP of the PV module varies for each value of irradiance and temperature, algorithms from Maximum Power Point Tracking (MPPT) are used. This tracking is carried out by varying the value of the useful cycle of a power converter [41].

There are currently a wide variety of Maximum Power Point Tracking algorithms as shown in [43], such as: Perturb and Observe (P&O), artificial neural network models such as RCC (Ripple Correlation Control) [44], incremental conductance (InCond) [45], among others. The complexity of these algorithms varies depending on the speed of convergence of the MPP, the different sensors used, the cost, etc. Due to the ease of operation, the P&O algorithm is the most widely used. It consists of modifying the duty cycle of the power converter (DC/DC) connected to the output of the photovoltaic string. This modifies the current drawn from the PV array and, therefore, the PV power obtained. This algorithm works by perturbing the voltage value of the PV array in one direction or the other until the power, or the product of the voltage and the current of the PV array, is maximised [46]. The PWM value of the useful cycle is used to vary the voltage of the PV string, the algorithm compares the current power with the previous one and on this basis determines whether to continue applying the same perturbation or to reverse it in the next cycle [41]. In ref. [38], it is mentioned that P&O algorithms require very low computational power but have some disadvantages, such as oscillation around the MPP point, which leads to a loss of efficiency, partial shadow conditions (PSC), the use of P&O algorithms [47,48], etc. In ref. [49], it is mentioned that this problem can be solved by reducing the step size. However, this is not a good solution as it implies slower MPP tracking.

According to ref. [37], currently there are no algorithms available that are able to accurately recognise the complexity of the shading condition and the resulting changes in the output of the PV power production system. In this study, the gap between simulation results and actual results is reduced by challenging the practical application of the Maximum Power Point Estimation (MPPE) algorithm. In PV systems, the non-conformity of the physical properties of the PV strings is the main cause of the difference between simulated and real results. The properties of PV strings can fluctuate drastically due to temperature, humidity, location or wear and tear over time.

Many studies can be found on the development of modified and improved P&O control algorithms. Several studies have been conducted to find suitable steps [50,51]. The two optimisation algorithms Particle Swarm Optimization (PSO) and the Earthquake Optimization Algorithm (EOA) were contrasted to obtain a higher energy efficiency. However, such algorithms for solving the optimisation problem are computationally intensive [52].

In ref. [38], it is shown that a large computational cost is required when using the incremental conductance (InCond) algorithms that look for voltage and current variations instead of power variations. However, it should be mentioned that these algorithms are fast and accurate. In ref. [53], they provided a variable-pitch IncCond, thus obtaining an improvement in steady-state performance. However, IncCond algorithms present the same behavioural problem with respect to the oscillation around the MPP.

The Reinforcement Learning (RL) technique is one of the most widely used techniques for MPPT controllers [38] because it is resistant to environmental variations [54]. Currently there are different types of RL agents. Evaluation of the benefits and disadvantages of using the methods table Q (RL-QT) and network Q (RL-QN) were discussed in ref. [55], where RL-QT showed less oscillation. In ref. [56], the two agents Deep Deterministic Policy Gradient (DDPG) and DQN, both with a P&O, were compared. The one that showed the best results in PSC conditions, the highest tracking speed and the highest energy achieved was the DDPG [57].

In ref. [38], they use the DT of a PV panel together with a DC/DC converter to train the controller set by a DDPG agent. The function of the RL algorithm and the DDPG agent is to produce references of the control signals, improving the performance of the controllers. Therefore, in this work we can see the simulated and implemented comparison between the traditional P&O control and the use of a DT together with the RL algorithm (DDPG) to control the MPPT.

In order to carry out the study of [37], a Digital Twin of the PV system is built to estimate the Global Maximum Power Point (GMPP), since the algorithms of Maximum Power Point Tracking (MPPT) cannot be guaranteed to obtain the GMPP. The aim is to eliminate or decrease the error between the real world and the simulation environment by using an artificial environment (a neural network).

Digital Twin (DT) Model

The DT model of [38] is based on mathematical equations that characterise the behaviour of the PV panel. Whereas in ref. [37], the DT of the PV module chain consists of a database of real values, the analytical model in MATLAB/Simulink and a neural network. In the following section, the DT model proposed by both studies is detailed.

In ref. [38], it is discussed that the use of a DT allows for the learning process to be sped up, allows for the abstraction of the environmental conditions and the simulation of any state. In addition, the maximum power can be used to complement the agent's reward function, thus optimising the whole learning process. The article also mentions that the use of a DT decreases the actual training time by 40.76%, as it allows for a higher simulation speed.

The characterisation of the photovoltaic panel can be seen in Figure 4, in this article the single diode model has been used [58].

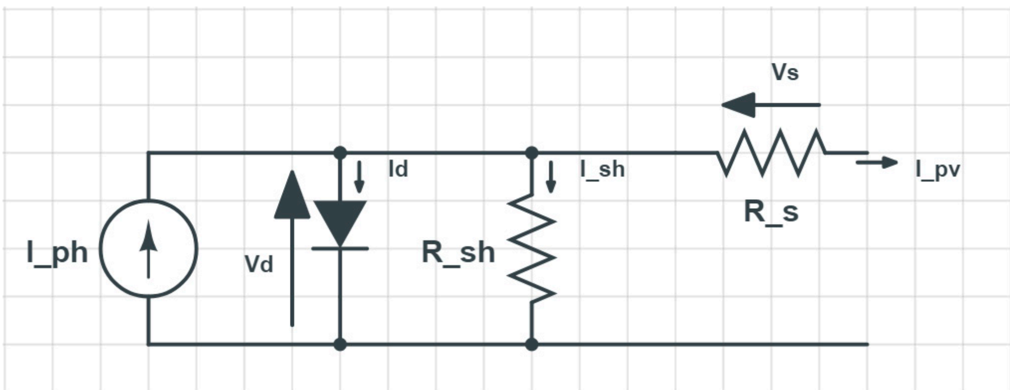

Figure 4. Schematic of the single diode model used. Source: Own elaboration based on the definitions and references in [38].

The equations obtained from the model in Figure 4 represent the mathematical equations for the Digital Twin used in [38]. They represent the output current and voltage of the PV installation, depending on the number of modules in parallel and in series.

In ref. [37], the first step is to construct a database with real values (x_{real}) by obtaining the shading matrix of real-world PV systems. This matrix is a vectorised description of the shading condition of the PV string [59]. With the data of the shading matrix, the position of the GMPP is extrapolated. While in the digital space (Matlab/Simulink), the PV system is created by generating an xsimulated database [60]. The gap between simulation and reality (the difference between the results of x_{real} and $x_{simulated}$) is modelled through a neural network. To obtain the MPPE results, x_{real} is assigned to x_{model} and the output is summed with the differences obtained from the neural network x_{nn}. This is the way in which the response of the DT is known, the response being the string voltage in the MPP (V_{pv}) (see Figure 5).

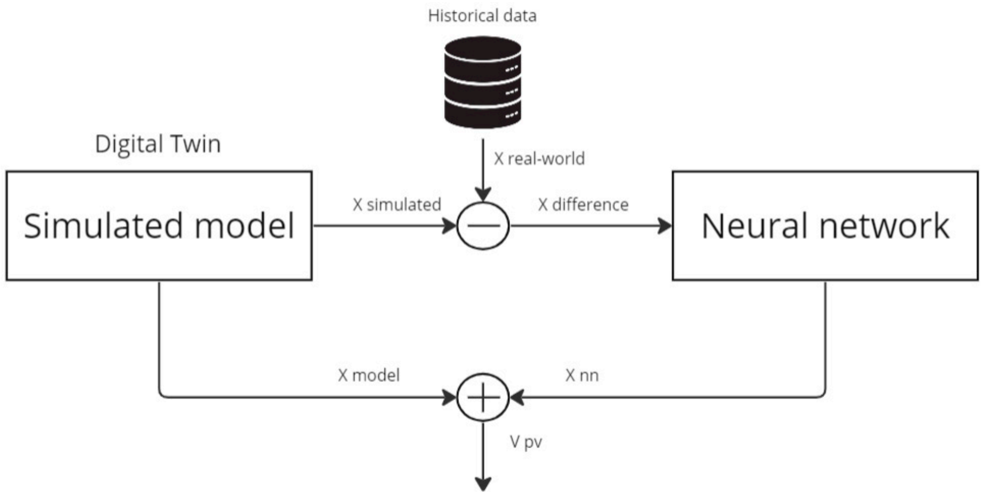

Figure 5. Schematic of the application of Digital Twin technology for the estimation of the maximum power point. Source: Own elaboration from definitions and references given in [37].

Simulation

In ref. [38], reinforcement learning (RL) was used with the DDPG agent which is described in the paper in great detail and is described below as written in that paper. In contrast, ref. [37] only mentions that a neural network was used without giving further details.

As mentioned above, the variable to be acted upon in [38] is the duty cycle of the converter. The Deep Deterministic Policy Gradient (DDPG) is used, as it allows for the use of deep learning with policy gradient models [61]. It is a stable and efficient algorithm.

Both papers use the MATLAB/Simulink environment to perform the simulations of their DT models. In the work of [38], they do not limit themselves to simulating the DT response, but also simulate the response of the real system using MicroLabBox DS1202. This is a multi-purpose rapid control prototyping system and a comprehensive platform that is specifically designed for laboratory use and can also produce analogue, digital and PWM signals.

Simulation, training and design in [38] was performed in Matlab and Simulink with the RL toolbox, version R2022b. Through the dSapce Controldesk 2022-B software, real-time data acquisition of the experiment was performed and imported into Matlab for processing and visualisation.

To carry out the training (see Figure 6), the controller receives the values of ambient temperature and irradiance, power output and duty cycle. The highest values and significant power variations are used in the reward function. They improve the training by evaluating the power with the highest value of the DT output power under the same circumstances.

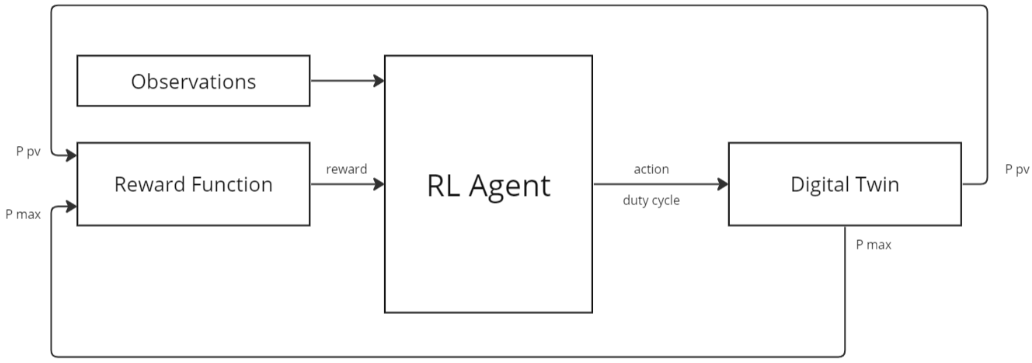

Figure 6. Schematic of the application of Digital Twin technology using the RL algorithm (DDPG) for the optimisation of the maximum power point. Source: Own elaboration from definitions and references given in [38].

Two simulations were performed, for testing the trained DDPG agent under different temperature and irradiance conditions. First with a fixed temperature and different irradiance and then simulating different temperatures at a fixed irradiance. Thus, its impact on the maximum power delivered by the PV module was observed. By doing so, the response of the DDPG agent to that of a P&O controller with a fixed step size can be compared to see if there is an improvement in the MPPT. In all cases, the simulations were performed with a fixed resistance in the DC/DC converter.

The simulation carried out in article [37] is carried out with MATLAB/Simulink to evaluate the proposed MPPE approach, which was described in the Digital Twin model section. In this case, by not using mathematical equations in their DT model and referring to their panel specification table, it is understood that the MATLAB/Simulink Electrical solar panel block has been used.

Testing in a Real Environment

It [38], MicroLabBox DS1202 was used to generate the PWM control signal with the appropriate duty cycle according to the RL algorithm (DDPG agent), to operate the PV module in its MPP. It is mentioned in [37] that in the PV strings they have taken data of the current, voltage and atmospheric conditions for five days, to check that in the DT model proposed by them (making the real PV string work at the voltage of the PV string obtained as DT response at the GMPP point) they manage to decrease the difference between the simulated and real results.

For the real environment test of the [38], a polycrystalline solar panel was used together with a boost converter. In this work, a sensor was used to receive irradiance and temperature data. The circuit was closed with variable resistors acting as an adjustable load to realise different experimental scenarios. Figure 7 shows a diagram of the hardware and the connections between the elements.

In [37], the PV panel model is not specified, only the characteristics table with the panel data under STC conditions is given. For the real environment test, a string of three and five PV modules were studied separately to obtain data in different environmental conditions. For five days, real-time data were collected from the panel strings using the PROVA PV system analyser. The analyser captures V-I data as well as atmospheric information.

Results

In the work of [38], it is shown that the DDPG agent is faster than the P&O, since the rate-limiting factor in reaching the MPP value is the DC/DC converter itself after receiving the PWM signal. All this can be seen in Figures 8 and 9, which are the simulation results at constant temperature and variable irradiance and under constant irradiance and variable temperature, respectively.

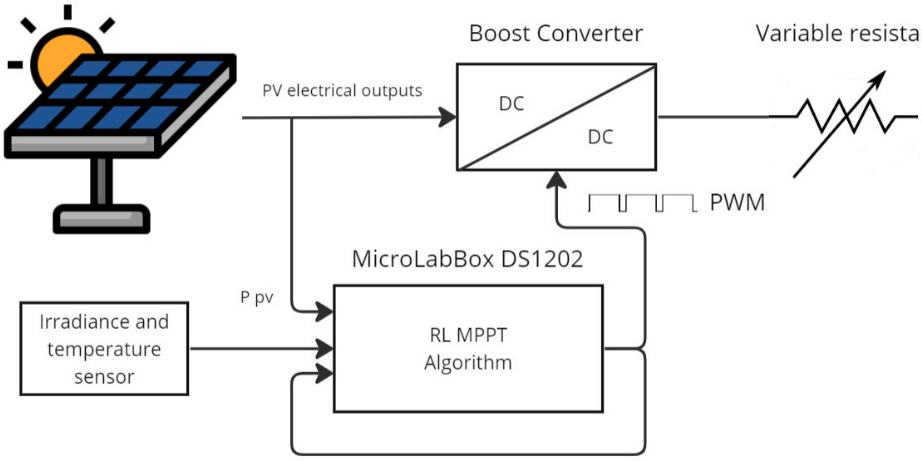

Figure 7. Schematic diagram of the hardware and wiring of the elements for the optimisation of the MPP search in [38]. Source: Own elaboration based on the definitions and references in [38].

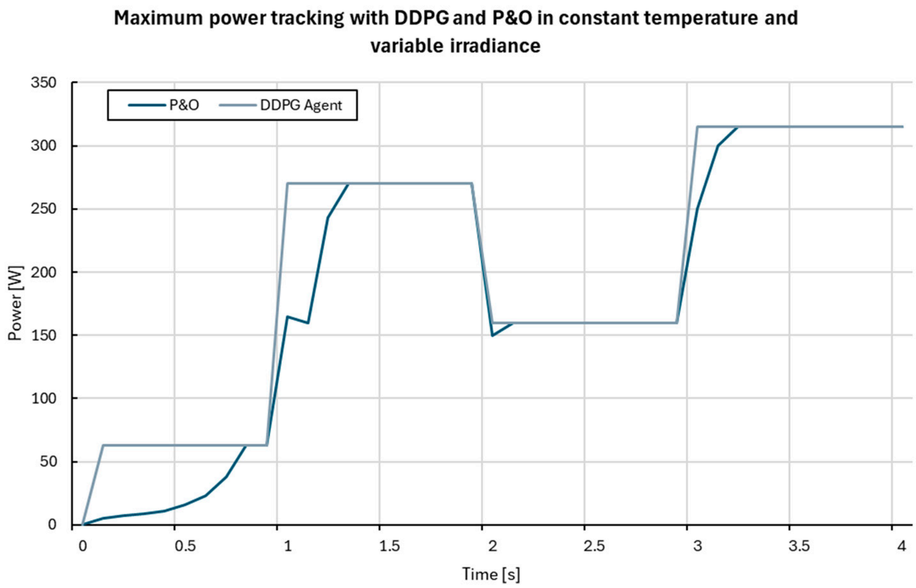

Figure 8. Plot of results obtained using DDPG and P&O algorithm at constant temperature and variable irradiance. Source: Own elaboration based on the definitions and references given in [38].

In the real environment, the experiments were conducted in the same way as in the simulations. For comparison of the solar panels, the controllers are operated one after the other in a short period of time to make the outdoor conditions more stable.

An efficiency improvement of 51.45% is obtained using the DDPG compared to the P&O. The article by [38] compares their work with similar work such as [56] where two similar simulations were performed, where an efficiency of 0.96% was obtained compared to 8.59% obtained in [38]. Another comparison is made with another work that also used neural networks, which is the reference [62]. The results obtained in [62] where they also propose their own method, but do not use a DT, are 5.2% compared to a traditional P&O. While in the work of [38], which does use a DT, an improvement of 10.45% is reached in [38] when compared to a traditional P&O.

It [37], a significant improvement is obtained with the proposed method, with 4% and 5% being the estimated error between the simulation model and the real world, respectively.

It should be noted that [38] focuses on finding the MPP for a panel, while the study by [37] does it for a string of PV panels looking for the GMPP. However, both studies contribute to the field of research in advancing MPPT algorithms by incorporating Digital

Twin technology and neural networks, providing improved performance compared to current MPPT algorithms and decreasing the gap between simulated and real results.

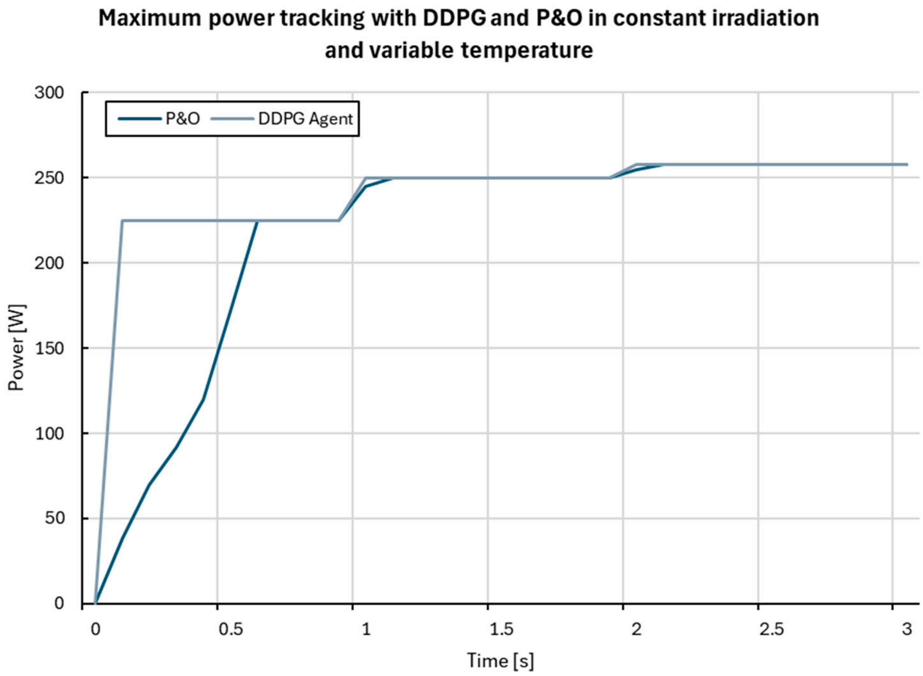

Figure 9. Plot of results obtained using DDPG and P&O algorithm at constant irradiance and variable temperature. Source: Own elaboration based on the definitions and references given in [38].

It [38], RL (DDPG agent) with a DT was used as the MPPT method of a solar PV panel, for comparing the results with the P&O controller. The proposed study was first simulated and then tested in a real environment. After the tests were carried out, it was shown that with the DDPG agent, both in the simulations and in the real environment tests, presented better results in finding the MPP. Furthermore, it did not present oscillations like the P&O.

Although the results are promising, in [38] it is stated that more depth and research is needed to conclude the effectiveness of the DDPG agent together with the DT of the PV panel. An important factor to consider, that poses a problem, is the weather dependency, as it is difficult to recreate scenarios in which it is possible to study the best way to improve the response of the controllers, as could be achieved in a controlled environment.

For future work, they mention in [38] that the combination of RL and DT techniques with other traditional optimisation methods should be investigated, and that the same should be tested as developed in this work, but not only for one PV panel, but for a string of PV panels.

It [37], the MPPE approach based on Digital Twins is studied and it is stated that the work carried out shows that the use of a DT to estimate the GMPP allows for the gap between simulation and reality to be decreased, and a better performance of the GMPP estimation is obtained. Table 1 shows a summary of what has been seen to this point.

4.3.2. Power Prediction

Today, renewable technologies are growing rapidly and are becoming increasingly efficient and competitive and are at the heart of the energy transition. Renewable energy forecasting enables the efficient management of renewable energy. With the increasing adoption of renewable energies and ongoing reforms in the energy market, the implementation of AI Grid (Smart Grid (SG), smart grid, intelligrid, Futuregrid, intergrid or intragrid) technology has become a prominent trend in the development of energy systems and represents an upgrade of the 20th century power grid [63].

This section reviews the article [40] and its use of a DT for energy forecasting in wind and photovoltaic systems. As the subject of this article is photovoltaic systems, only the study of the photovoltaic system will be discussed.

Table 1. Optimisation of the search for the maximum power point.

Reference	Photovoltaic System under Study	Input Data to the WP	Sensors for Input Data	Mathematical Equations of the DT Model	Model DT	Data Output from the DT	Neural Network Models in Simulation	Testing in a Real Environment	Result
[38]	A photovoltaic panel.	Temperature and irradiance.	Yes (irradiance and temperature sensor).	Yes.	Mathematical modelling in MATLAB/Simulink.	Power of the photovoltaic module.	Training of the reinforcement learning (RL) method with the DDPG agent.	A solar panel together with a boost converter and a variable resistor.	Estimation of the maximum power point of a solar panel.
[37]	String of photovoltaic panels.	Temperature and irradiance.	Yes (PROVA PV system analyser).	No.	Renewable energy block diagram, MATLAB/Simulink Simscape Electrical and a neural network.	Chain tension at maximum power point.	Training of a neural network (the article only mentions a neural network, without giving further details).	Three and five PV strings.	Global Maximum Power Point (GMPP) estimation.

In [40], A Digital Twins power forecasting platform for an AI Grid is proposed [10]. Based on the historical data of power load and weather conditions, it is proposed that [40] the platform predicts wind and PV power generation for a given date; thus, providing a platform that supports end-consumers in the electricity market when making consumption decisions, enabling better management of the electricity system.

In short, the work of [40] consisted of the creation of a real PV and wind generation database through Elia Open Renewable Energy Generation (Elia Transmission Belgium operates the electricity transmission grid in Belgium), the development of the load power forecasting model and finally the visualisation through the DT module.

In the work of [39], two complementary approaches for the energy prediction of a solar panel are presented. These approaches are carried out using the object-oriented modelling language Modelica and the model Long Short-Term Memory (LSTM).

Digital Twin (DT) Model

The work of [40] presents a Digital Twins power forecasting platform for AI Grids, using the DT model to create a realistic simulation environment as well as accurate forecasting of wind and PV loads.

The DT model proposed in this work consists of creating a 3D model of the PV plant (data collection and creation of the 3D Digital Twin) and an intuitive interface with the prediction results. Periodically, polling requests are sent to the server to update the view in real time.

In 3D digital space, a real PV plant is modelled as a research scenario with the 3DSMAX program. At the same time, Blender 3.4 is used for a more refined model.

The platform developed for the visualisation of the DT updates the data and graphs of the interface in real time. It is a very intuitive platform that allows for the selection of the desired forecast date and visualization of the predicted results, see Figure 10. This platform allows for data analysis and forecasting, contributing to an improvement in the management and optimisation of PV power generation plants.

In [39], the DT approach using Modelica consists of a physical-numerical model, based on mathematical equations representing the behaviour of the solar panel. The second approach is based on a machine learning algorithm (LSTM), which is trained with historical data on temperature, irradiance and energy production.

For data updates in the digital twin platform, the server periodically sends updated data retrieved from the cloud, with data from the WPNet model results sent by the local server to the cloud.

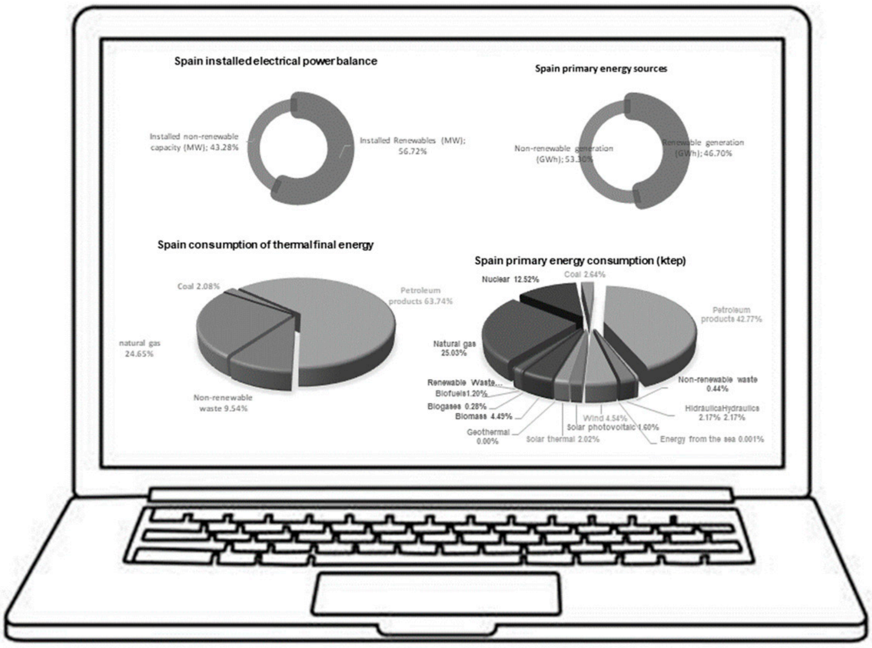

Figure 10. Digital Twin Platform for power forecasting developed in [40]. Source: Own elaboration from definitions and references given in [38].

Simulation

From the literature review in [40], regarding power forecasting models in photovoltaic systems [64,65], it is concluded that the best results were obtained with the deep learning approach. Furthermore, it is concluded that most of the current deep learning algorithms are used to predict power loads of non-renewable energy sources [66–69], and that studies related to the prediction of renewable energy based on meteorological data are scarce; therefore, in this study, the WPNet model based on deep learning was developed. This model first has the data processing layer, another GRU layer, and finally the Dense layer.

The power generated by a photovoltaic installation is mainly determined by irradiance and temperature. Current prediction models do not provide accurate forecasts of environmental conditions.

In [40], more than eighteen thousand PV generated log data points and weather conditions from the year 2021 to the year 2023, from the Belgian regions of Flanders and Wallonia were used. The data was taken from Elia Open Renewable Energy Generation and a filtered real PV load power database was constructed for forecasting. The data used were PV power, wind power and generation impact factor. On the other hand, meteorological data were taken from Brussels.

As mentioned above, the WPNet model was used to carry out the prediction model. The metrics used to evaluate this method were the mean squared error (MSE), the absolute mean squared error (MAE) and the radical root mean squared error (RMSE).

Simulation of the two approaches proposed in [39] was carried out in the Modelica simulation environment.

Results

In the simulations carried out in [40], the proposed WPNet model was compared with other load power forecasting models, including the Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), Attention and Transformer models. The load power data and weather conditions were used as simulation inputs to obtain the predicted load power values. The results obtained from the model proposed in [40] provide results with higher accuracy than the other models.

After filtering and processing the meteorological data, the WPNet model was used to predict the power at different time intervals, and these were sent to the Digital Twin model visualization platform.

All in all, good results were achieved with the use of DT technology for wind and PV forecasting, but the limitations, and therefore future lines of work for this study, will be the study of failures and scale changes in equipment, for more accurate forecasting of renewable energy using DT technology, with the aim of contributing to the optimal operation of smart grids and better planning decisions. The results of the two approaches proposed in [39] show that with respected to the model's ability to predict the hourly frequency during the day, the worst model is LSTM, while for RMSE values, the worst model is the one based entirely on mathematical equations in Modelica. Table 2 shows a summary of this point.

4.3.3. Energy Management in Buildings

An important point in a microgrid is the balance between production and load, where users participate in achieving this balance [70]. In order for users to engage in load shifting, several demand response schemes need to be implemented [71]. Price-based demand response is one of the main points to be studied. Algorithms and automation technologies are also needed to schedule loads. There are several publications in this field, such as [72,73], where the scheduling of domestic energy use and the scheduling of energy management of different loads were studied, respectively.

In the article under consideration, which is [32], the user's preferences are taken into account in the scheduling of the load, as in [74–76]. In [32], the uncertainty associated with solar irradiance has been taken into account, unlike in article [77], where a residential load management system using distributed generation sources is proposed.

The RL algorithm was used in [32] to perform several simulations in order to schedule loads with the lowest daily cost of electricity, efficiently using PV and grid-sourced energy taking into account the user's load operation preferences. The article provides a mathematical formulation, the use of the Beta probability density function, to model the uncertainty of PV production and the development of an algorithm using the Digital Twin model, to minimise energy bills by including renewable energy resources for load scheduling.

The aim of the study in [33] was to seek to balance energy generation and demand in buildings with an innovative approach by creating a DT from solar PV energy production. The PV system under study is a two-panel PV system located on the rooftop of the renewable energy research laboratory at the University of Sharjah. Energy production predictions are made 15 min in advance using the LSTM network, as well as an application with MATLAB APP Designer to visualise the performance of the Digital Twin, allowing for the anticipation of energy imbalances.

Digital Twin (DT) Model

The DT approach proposed in [32] consists of a multi-layered framework for processing and collecting information with a bidirectional flow, thus differing it from centralised processing methods seen in [78,79]. The suggested multi-layer method in [32], which is explained below, seeks to reduce the peak power demand, and provide a rate optimisation and configuration of the central power control parameters of the upper layer of the suggested DT.

The upper layer is called the Electric Digital Twin (EDT), which represents the electrical control centre. In this layer, the central controller adjusts the billing after receiving the consumption data from the lower layer.

The lower layer of the DT of each smart home is referred to in this article as the Home Hk Digital Twin (HDTk). In this layer, the local smart home controller collects information and data from the upper layer of the Digital Twin (EDT) and the devices in the home, and uses this information to represent a digital replica of the behaviour of the devices in the home. In addition, it takes into account user preferences and expected energy prices, the aim of which is to improve the energy consumption patterns of the replicas of the electrical devices.

The data that are collected to create the replica of the devices in the home is done through the IoT, so that the hourly energy consumption is known. If this data reading is not possible, as mentioned in the article, the information from the device's data sheet is used, obtaining what they call the nominal energy use.

In a neighbourhood, each HDT in each household estimates the best consumption periods for each device based on the user's consumption habits and preferences.

The DT model of the photovoltaic installation studied in [33] consisted of two 335 W panels placed in series and was carried out with the renewable energy block diagram, using MATLAB/Simulink Simscape Electrical.

Simulation

To integrate PV into the load scheduling, a stochastic model is created due to the unpredictable nature of solar radiation. The implementation of the Beta distribution function (Beta PDF) has been chosen from previous data collected over a year studying hourly solar radiation, in order to capture the random behaviour of this resource [80]. PV modules generate power as a function of solar radiation, ambient temperature and module characteristics. Using the associated PDF Beta, the solar irradiance for a given hour is determined. The photovoltaic power (PS) of the element analysed here is obtained as a function of the estimated irradiance and by means of mathematical equations. This power is used for load scheduling with distributed generation (DG).

The mathematical model they provide to solve the LCP load scheduling problem aims to minimise the economic cost of total electricity in a day by taking into account the degree of inconvenience to the user due to the delay in the load operation. The problem formulation is formulated for the case of no resource as well as for the case of n resources, such as photovoltaics, grids, wind turbines and energy storage.

In formulating the problem, they took into account the number of loads in a household, the temporal division of the day into 24 time periods (k = 1, . . ., 24), the load operation interval (start and end time of load operation), the duration of load operation and the rated power in kW of the load. In addition, they introduced the parameter udc to capture the degree of user discomfort when there were delays in operation, such as in the operation of a washing machine. A low udc value indicates comfort with the delay, while a high udc value indicates the opposite, leading to higher energy costs.

To carry out the simulations, an RL algorithm using DG is developed for a grid-connected house with PV installation, data and performance specifications for each load. The objective of the RL algorithm is to minimise the daily cost of electricity using two resources, PV and grid, taking into account the user's preferences. The aim is to reduce the energy cost in each hourly interval of each day, for each type of resource.

In addition, preferences are assigned to appliances according to consumption priorities, knowing which appliance the user accepts if there is a delay in its operation. We studied and took into account the energy use patterns that may exist in a neighbourhood depending on the type of users, in order to know, among other parameters, the peak time of highest consumption.

In [32], several simulation tests were performed evaluating and testing the flexibility of the designed algorithm for the load scheduling problem (LCP) using RL both in the case of having and not having DG, and the results of these simulations are detailed in the results section.

In [33], long-term memory networks (LSTM) were used, with an irradiance and temperature data period of two-weeks (a part of the recorded historical data). Simulation of the DC power generated every 15 min was performed in MATLAB and Simulink.

Testing in a Real Environment

The work of [32] was completely simulated, they have not performed any tests in a real environment using a Digital Twin based algorithm.

For the test in a real-life situation see [33], where a rooftop installation of the renewable energy laboratory of the University of Sharjah was used. The Profitest measuring device was used to receive power, inclined global irradiance and module temperature data every 15 min from the installation. In addition, what is actually consumed in the laboratory was compared with what was generated by the photovoltaic installation, to obtain a variable to evaluate this difference. In this way, the possibility of achieving NZEB buildings in the renewable energy laboratory was evaluated.

Results

First, they tested 6 loads, dispensing with the photovoltaic power source in the simulation. The loads were programmed in a low-energy price range. In the simulations, different udc values were used to study their effects, and it was concluded that increasing the udc value, i.e., when comfort is a priority and delays in operation are not accepted, leads to a higher energy price.

A differential tariff was then selected and 100 random loads were created with a load generator to check and validate the results according to the udc values based on their operating hours. The operating intervals of the loads were randomised. Subsequently, in this work, the results obtained by applying the Digital Twin technology were evaluated with those of the LA algorithm in [81], where the RL algorithm of [32] presents a lower computational time.

The next scenario they simulate included the PV resource, and the randomness of the solar radiation is represented using the Beta distribution function, so that the RL algorithm learns at each iteration. They performed the same procedure, first with 6 loads, and then with 100 random loads. In this scenario, the energy cost decreased, as well as the energy consumption of the grid. In addition, the usage time using the RL is higher as more actions are performed.

Another simulation scenario was the investigation of the efficiency of the suggested scheduling algorithm using a small microgrid with scheduled and unscheduled residential devices, and also a PV resource. Initially, the DG resource was not taken into account in the analysis.

The simulation was compared with the grey wolf optimisation algorithm (GWOA) [82] (Ch. 72), with residential loads from the proposed RL algorithm. A similar minimum price is obtained in the two simulations. The GWOA algorithm requires more computational time and presents more difficulty when PV resources are present than the RL algorithm using the Beta probability density function.

The results of [33] indicate that the electricity production forecast of the developed LSTM network are reliable (R = 0.99831). The balance between demand and consumption in the laboratory has been studied and it has been determined that the current installation does not cover the demand of the renewable energy laboratory. Table 3 shows a summary of this point.

Table 2. Power prediction.

Reference	Photovoltaic System under Study	Input Data to the WP	Sensors for Input Data	Mathematical Equations of the DT Model	Model DT	Data Output from the DT	Neural Network Models in Simulation	Testing in a Real Environment	Result
[40]	Grid-connected photovoltaic installation.	1. History of actual PV and wind power at national level from the national database. 2. Historical national temperature and irradiance data from the national database.	No.	No.	Wind and PV forecasting platform on a regional scale, for two regions in Belgium.	1. 3D model of the photovoltaic and wind power plant. 2. Intuitive interface with predictive results.	WPNet, LSTM, CNN, Attention and Transformer models.	No.	1. Prediction of wind and photovoltaic generation for a given date in two regions of Belgium. 2. Development of WPNet's own forecasting model.
[39]	A solar panel.	The ambient temperature, the magnitude of the wind speed and the incident solar radiation.	No.	Yes.	Physical-numerical model built in Modelica.	Panel current, panel voltage and power.	LSTM long-term memory network model.	No.	Simulation and prediction of the energy produced by photovoltaic panels.

Table 3. Energy management in buildings.

Reference	Photovoltaic System under Study	Input Data to the WP	Sensors for Input Data	Mathematical Equations of the DT Model	Model DT	Data Output from the DT	Neural Network Models in Simulation	Testing in a Real Environment	Result
[32]	Smart house with grid-connected photovoltaic system.	Solar radiation and temperature estimated using the Beta distribution function with one year's historical data for radiation and temperature.	No.	Yes.	Multi-layer DT model in Smart Grid. The Electrical Digital Twin (top layer) represents the electrical control centre and the Domestic Digital Twin (bottom layer) represents the digital replication of the smart home devices.	Estimation of the photovoltaic power of the smart home.	RL model, LA and the GWOA algorithm.	No. All results were performed in simulation.	Algorithm for scheduling the operation of residential loads at the lowest electricity cost.
[33]	Grid-connected photovoltaic system	Temperature and irradiance.	Yes (Profitest measuring device).	No.	Renewable energy block diagram, MATLAB/Simulink Simscape Electrical.	Planned photovoltaic power.	LSTM model.	Photovoltaic system with two 335 W panels in series	Balance between energy generation (solar PV) and demand (energy consumption of buildings).

4.3.4. Fault Detection in Distributed Photovoltaic Systems

There are many articles studying how faults in photovoltaic installations affect performance and safety, e.g., in [83,84]. Therefore, many other studies investigate the detection and diagnosis of failures of different components in photovoltaic systems [85–89], such as solar panel breakage (micro-cracks), broken solar cells or bypass diodes, wiring failures, potential induced degradation (PID) and short-circuit problems in power converters [88,89]. Work on the detection and classification of faults in PV installations using artificial intelligence techniques has been increasing [90–92], and not all studies include a system to alert the user when a failure occurs [69–72]. In [22], it was reported that DT technology was used for the operation and maintenance of solar energy systems, according to several studies, or the life cycle management of the solar plant [93], or for the monitoring of decentralised renewable energy sources [94].

This section compares the articles [22,35,36] in their approach to using a DT for fault diagnosis in a PV system.

In the article [35], it is mentioned that there is little research on fault diagnosis in a complete PVECU (a PV panel together with a power converter). Hence, there was a need for their study, in which they carried out a Digital Twin approach for fault diagnosis in a distributed PV system based on power electronics. For each PVECU a fault diagnosis was performed, comparing the output of the Digital Twin and the physical model and obtaining a residual vector whose values allowed for the detection and identification of the fault. The proposed approach was tested in a real environment and carried out in an FPGA to demonstrate the effectiveness of being able to detect up to ten different types of faults and distinguish whether they were faults in the PV panel, in the power converter at panel level or faults in the electrical sensors. In short, the paper explains how a prototype source-level power converter has been developed and designed to create a fault detection and identification system for a distributed PV system.

A novel Deep Learning method is presented in [36], developed a PV fault detection method using the Digital Twin (DT) model, a convolutional mixer (ConvMixer) for fault classification, and all this together with a long-range notification (LoRa) system. Using the Markov transition field transform (MTF), 2D images with the simulated PV faults were generated and used as input to the ConvMixer. The PV system studied in this work is a 49 kW grid-connected system at Chung Yuan Christian University, Taoyuan, Taiwan.

The real-time simulation to verify the effectiveness of the proposed method of integrating DT for fault detection, and ConvMixer for calibration together with the LoRa notification system, was carried out with Opal-RT eMegasim (real-time digital simulator representing the real PV installation).

An innovative approach to TD applied to photovoltaic installations was proposed, mainly aimed at the operation and maintenance of photovoltaic installations. In [22], it was proposed to create the DT of each component of the PV installation (PV panel, DC converter and final power output of the system or grid as mentioned in the paper) and not a general DT model of the whole system. In this way, a better knowledge of the state of each component and efficient fault detection was sought. The behaviour of the PV system was predicted by training three different machine learning algorithms (random forest regression, deep neural network regression and catboost regression), thus being able to detect component malfunctions.

Digital Twin (DT) Model

In all three papers, the DT model takes into account the meteorological conditions of temperature and irradiance as inputs. In [35,36], mathematical equations were used to model the DT and consider the entire PV installation in which they do the DT. While the third one, ref. [22] used a DT approach for each part of the PV system. It is worth differentiating that in the first one the simulation of the digital twin was performed in MATLB/Simulink and in the second in Python 3.7. In contrast, the DT model proposed in [22], which consisted of creating DTs of each part of the PV installation (PV panel, DC converter and grid), used the PV panel, converter and grid blocks that come with MATLAB/Simulink Electrical. In both cases, the output of the real system was compared with the output of the digital system for fault detection.

The DT model presented in [35] is represented by a set of equations that model the behaviour of a PVECU with a four-switch step-down power electronic converter. The choice of such a converter was based, among many others, on [95], because it allows greater flexibility in the number of panels in series with a higher efficiency. The DT response as a function of temperature and irradiance conditions contains information about the state of the power converter (power converter inductor current and power converter capacitor voltage), the current and voltage of the solar panels at the MPP point, as well as the sensor gains represented in an identity matrix. The paper further ensures that the solar panel current and voltage equations were within $\pm 5\%$ error. The DT simulation was performed in MATLAB/Simulink.

In [36], a DT model based on mathematical equations was used [96] for PV fault detection, which was implemented in Python 3.7. They performed PV fault detection by comparing the PV power of the output DC arrays of the physical system and the digital system. In [36], they indicated that they consider that there is a fault when the difference of the DC power of the actual PV array and that of the DT is less than 0.5% of the DC power of the DT PV array. The physical system was implemented in Opal-RT, as will be explained in the real environment testing section, and the DT receives the temperature and irradiance data through the data sent by Opal-RT and the user diagram protocol (UDP). Once the fault is detected, the Python program uses the ConvMixer previously trained in Matlab/Simulink for fault classification.

The DT approach for each component of the PV system (PV panel, DC converter and grid) in the work of [22] consists of creating a single platform in which you have all of the information necessary for the operation and maintenance of the grid-connected PV system. The proposed platform was developed on Docker (an open-source platform that encapsulates applications, facilitating software development and deployment). They created a REST API to interact with the outside and receive irradiance and temperature data, as well as data from the MATLAB/Simulink PV installation and prediction models. They used the skitlearn framework and keras for machine learning, prediction and retraining, and commands are received via the Redis database. The Inlux DB database was used to store the time-series data. The DT approach proposed in [22] was visualised in Grafana (a free software that allows for the visualisation of graphs from multiple sources such as Inlux DB, etc.). The objective of the DT was for the trained model to be used to predict how each component of the PV system would behave and compare it with the real behaviour, thus being able to know if there were any deviations and possible failures in the installation. The failure signal is sent to the user when there is a 20% difference between the response of the real twin and the Digital Twin.

Simulation

In [22,36], neural network models were trained in the simulation to be able to differentiate the type of fault occurring, while in [35], a library of faults induced in the simulated PV system was created. In all three works, MATLAB/Simulink was used to perform the simulation and differentiate the type of fault. From the works that used neural networks, ref. [36] presented an innovative proprietary method developed for fault identification. In contrast, in [22], three existing models were tested to determine which provided the best result. The study by [22,36] was fully simulated, to give a closer approximation to the real environment in [36], using the real-time digital simulator Opal-RT eMegasim.

The fault detection methodology proposed in [35] consists of digitally comparing the output of the physical system in real time with the output of the DT (the output values of the real system are subtracted from the output values of the DT), so that when there are no faults both outputs are equal, thus generating an error vector. To put all of this into practice, and to be able to differentiate the type of fault that can occur in the PVECU, they used the

MATLAB/Simulink electrical circuit simulation toolbox to study and create a library of faults, according to the responses of the DT to the faults induced in the simulation. In the study of [35], neural networks are not used. In the MATLAB/Simulink simulations they simulated different types of faults and observed the responses of the DT. Thus, it could be observed that each type of fault evolves and takes a different direction in space, thus being able to create a library with 16 different types of faults, related to the solar panel, the converter and the sensor. To test the fault detection and diagnosis approach, a PV system was simulated with two PVECUs connected in series, each with its own control and monitoring system. The simulation showed good results, so the next step was testing in a real environment.

In [36], they presented a new Deep Learning method, the convolutional mixer (ConvMixer), which receives DC PV power output data from the array in the form of 2D images; such data-to-image transformation is performed when using the Markov transition field transform (MTF). It is mentioned in [36] that this method adapts and learns quickly under changing conditions. One convolution layer is used to position the images in space and the other to mix the channel information. The results of the PV power value at the output of the DC converter in the PV fault simulation in MATLAB/Simulink were fed into the MTF, which converted them into 2D images. Once the 2D images were obtained, they were fed into the ConvMixer for training. Thus, the ConMixer was trained in Matlab/Simulink to be able to classify the faults.

The ConvMixer training in [36] was performed in MATLAB/Simulink to simulate and detect line-to-line, panel open circuit, panel short circuit, open string, shorted string and partial shading faults. The power value of the PV array after the converter was used to create 2D images with the MTF which then used these images to feed into and train the ConvMixer. The PV system studied [36] was implemented in Opal-RT and MATLAB/Simulink (version 2018a). Thus, a real-time simulation was performed for the diagnosis, classification and fault reporting of the installation under study. As already mentioned in the section on the Digital Twin model, the DT model of the photovoltaic installation to be studied was created in the Python program, which receives, via UDP communication with the physical model, the data on temperature, irradiance and power output of the DC photovoltaic array for comparison and detection of possible faults in the installation. Then, with the ConvMixer trained in MATLAB/Simulink and loaded into the Python program, the faults are classified. Once the faults have been classified, they are sent to the LoRa gateway and from there they are sent to NodeRed (a programming tool that allows for the connection of hardware devices, online services and APIs in real time), and from there it is connected to IFTTT (a web service for programming actions for the automation of different actions and tasks online), for the notification of the fault to the user.

In the research of [22], the use of Digital Twin technology compared three algorithms from machine learning (ML), Deep Neural Networks (DNN), Random Forest (RF) and CatBoost. In [22], the MATLAB/Simulink PV installation plant was created to train the ML models. First, the meteorological data of several years were obtained from PVGIS and then some of them were used in the simulation of the PV installation, thus obtaining the experimental data to train the ML models. Since, as mentioned in the article itself, no data from a real installation was available, they had to use the model data in MATLAB/Simulink as if it were a real installation in order to train the ML models. At each step, they built containers with Docker, these being Influx DB, ML, Redis, FastAPI and Grafana.

Testing in a Real Environment

The real environment test in [35] was performed using the DC converter designed and developed in that work, where all the simulated fault detection and identification logic, as well as the library created in the simulation, was loaded on a FPGA. In [36], a hardware emulator of the PV plant was used in the laboratory (Opal-RT), so it was not carried out in an authentic real environment. The study of [22] was fully simulated.

On the roof of a building on the campus of the National University of Singapore, they used a 260 W photovoltaic panel to which the 120 mm × 100 mm prototype was connected at the back to test it in a real environment. The 300 W step-down converter-rebooster prototype was realised on the Artix-7 FPGA. A weather station was used to receive temperature and irradiance data. The DT model, the fault detection and identification methodology, as well as the fault library that was developed, were implemented on the Artix-7 FPGA. In addition, they included the MPP tracking of the solar panel according to [97] in the control logic.

The PV system in [36], connected to the grid of Chung Yuan Christian University, Taoyuan, Taiwan, was the object of study. However, no tests were performed in the real installation environment, and all measurements and tests to demonstrate the effectiveness of the proposed fault classification detection study were carried out using Opal-RT together with MATLAB/Simulink.

The study of [22] was fully simulated, as indicated in the article itself.

Results

In the real environment, the different types of faults that had been recorded in the fault library were tested, taking into account that the detection and identification of faults in the prototype, either in the PV panel, in the converter or in the sensors (panel current, panel voltage and converter inductor current sensors), can only be performed for the faults found in the fault library. The detection time for faults in the PV panel was the longest and the shortest detection time was due to faults in the sensors. In [35], a comparative table with other works is presented. The main conclusions they draw from this comparison was that the other works did not have a general application approach and the use of the Digital Twin technology, as is the case in [35], can be applied to other energy conversion systems, and that the ability to detect and identify faults up to the date of the study (January 2020) had not been achieved by other studies [98–101]. In addition, they mention that this DT model proposed in [35] is applicable to other energy systems.

With the simulation results of [36] using Digital Twin technology, it was shown that their proposed ConvMixer method for classifying faults in PV installations performed better than the random forest, the decision tree, as well as other CNN-based methods. Furthermore, it is highlighted that the computational cost of the proposed method compared to the other CNN methods is lower. For the fault classification, the obtained results were very good in general (97.00% in the accuracy tests), indicating that there was a small amount of confusion in the line to line faults and open circuit faults in the panel, but that this did not influence the overall performance of the proposed model.

In the simulation results using the Digital Twin technology in [22], in a Matlab/Simulink of a 150 kW power PV plant, the root mean square error (RMSE) and mean absolute error (MAE) values were obtained for each ML model and for each part of the PV system or for each DT created, i.e., for the solar panel, the DC converter and the power grid. In the case of the PV panel, the performance of the panel was studied as a function of weather conditions. The deep regression neural network (DNN) model had the lowest prediction error and the catboost had the highest. For the DC-DC converter, taking into account the difficulty of modelling using ML models, the Random Forest (RF) model showed the best results, while the opposite was true for DNN. For the power grid part, the inputs were the outputs of the DC converter, and the evaluation of the power output of the system they obtained showed that all three methods were very good and had practically the same RMSE and MAE values. However, in the latter case, they chose catboost, as they used size, speed and complexity of the model as criteria. Table 4 shows a summary of this point.

After the analysis in this section, it can be said that there is no standard for applying the Digital Twin in PV installations. Depending on the preferences and needs of each study, different models of Digital Twins can be used to study solar PV systems for different purposes. This can be both an advantage, as this technology can be used in a flexible way, and a disadvantage, as there are already established standards for the inexperienced user who wants to use this technology in PV installations. At this point, it has been shown that a DT can be used to optimise the production of renewable energy, predict the PV energy generated, manage energy in buildings or to detect and classify faults in PV installations. However, regardless of the use of the Digital Twin, the input data of the Digital Twin has to be at least the ambient temperature and the irradiance to which the actual PV installation is exposed. It can also be said that there is no standard communication protocol for sending, receiving and storing data.

The use of DT technology in PV installations allows for significant improvements in MPP search and GMPP estimation. The use of this technology together with new or existing neural network models provides better results in the prediction of PV renewable energy generation. This leads to better management of PV renewable energy. In addition, the studies reviewed in this article that use DT technology together with different neural network models for fault classification show very good results.

There is arguably a need for more studies to investigate the combination of reinforcement learning techniques and the use of Digital Twins with other traditional control optimisation methods. One of the main drawbacks of using a Digital Twin in PV installations is the dependence on environmental conditions, which makes it difficult to recreate different scenarios to simulate PV renewable energy using a DT. Many of the articles reviewed in this section only focus on the theoretical design of applying the DT to PV installations for different purposes, but without testing it in a real environment.

Table 4. Fault detection in distributed PV systems.

Reference	Photovoltaic System under Study	Input Data to the WP	Sensors for Input Data	Mathematical Equations of the DT Model	Model DT	Data Output from the DT	Fault Detection	Classification of Failures	Neural Network Models in Simulation	Testing in a Real Environment	Result
[35]	PVECU complete photovoltaic energy conversion unit (a photovoltaic panel together with a power converter).	Temperature and solar irradiation.	Yes (pyranometer and temperature sensor).	Yes.	Mathematical modelling of the whole system in MATLB/Simulink.	Panel current, panel voltage and DC converter inductor current.	Comparison of the response of the real system and the DT.	Creation of a fault library with simulation results.	The simulation was carried out in MATLB/Simulink without using neural networks.	A PVECU unit on the roof of a building on the campus of the National University of Singapore.	Development and design of a prototype source level power converter to create a fault detection and identification system for a distributed photovoltaic system.
[36]	49 kW grid-connected photovoltaic system.	Temperature and solar irradiation.	Yes (Opal-RT eMegasim real-time simulator data).	Yes.	Mathematical modelling of the whole system in Python.	Photovoltaic energy.	Comparison of the response of the real system and the DT.	Training of neural networks in MAT-LAB/Simulink.	A novel Deep Learning ConvMixer method has been developed to classify faults.	No. The Opal-RT eMegasim real-time simulator has been used to validate the results.	Photovoltaic fault detection, classification and warning system. As well as the development of a new Deep Learning method (ConvMixer) for fault classification.
[22]	150 kW grid-connected photovoltaic plant.	Historical temperature and irradiance data from the PVGIS database.	No.	No.	DT of each part of the PV system (solar panel, DC converter and final system/grid output power) with blocks in MATLB/Simulink Simscape Electrical.	Planned photovoltaic power.	Comparison of the response of the real system and the DT.	Training of neural networks in MAT-LAB/Simulink.	The regression models are Deep Neural Networks (DNN), Random Forest (RF) and CatBoost.	No.	Visualisation platform with operation and maintenance information for each DT of the photovoltaic installation. The performance of the PV system is predicted.

5. Conclusions

This article has analysed the Digital Twin concept, the parts that compose it, the different types of Digital Twins, their applications in different sectors and benefits in general. Subsequently, the bibliography on the use of DT technology applied to PV installations has been analysed, analysing how the use of the Digital Twin has been carried out in these installations and evaluating the improvements that such use entails. The literature reviewed in this study indicates that DT technology is applied in PV systems to improve the energy management system in buildings, the optimisation of the MPP of PV panels, the prediction of the power generated and for the detection and classification of faults. Investing in the application of DT technology in PV installations therefore represents a positive return on investment. It will reduce operating and maintenance costs, as well as improve the overall performance of the PV system. An important aspect of a DT is that by providing real-time data and analysis, it enables better decision making in the face of changing challenges in the solar PV sector.

From this previous study included in this work, our research group will apply Digital Twin technology to the versatile PV installation located at the Escuela Técnica Superior de Ingeniería Industrial of the University of Extremadura in Badajoz (Spain). In order to study this installation, the strategic decision making in terms of improving the management of PV renewable energy generated and consumed, as well as the detection of failures in the PV installation will be considered. Furthermore, we will evaluate options such as total self-consumption, the use of the battery or the consumption of energy from the grid, considering the type of day and the time slot to optimise the efficiency and profitability of the system.

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Nomenclature

MPPT	Maximum Power Point Tracking
P_{MPP}	Maximum PV module power
P&O	Perturb and Observe
MPPT	Maximum Power Point Tracking
RCC	Ripple Correlation Control
PSO	Particle Swarm Optimization
EOA	Earthquake Optimization Algorithm
InCond	Incremental Conductance Algorithms
RL	Reinforcement Learning
RL-QT	Table Q
RL-QN	Network Q
DDPG	Deep Deterministic Policy Gradient

MSE	Mean square error
MAE	Mean absolute root mean square error
RMSE	Radical root mean square error
LSTM	Long Short-Term Memory
GWOA	Grey Wolf Optimisation Algorithm
ConvMixer	Convolutional mixer
LoRa	Long Range Notification
MTF	Markov Transition
ML	Machine Learning
DNN	Deep Neural Networks
RF	Random Forest

References

1. International Renewable Energy Agency; Global Renewables Alliance. Global Renewables Alliance Tripling Renewable Power and Doubling Energy Efficiency by 2030 Crucial Steps towards 1.5 °C. [Online]. Available online: www.globalrenewablesalliance.org/ (accessed on 10 February 2024).
2. Liu, X.; Jiang, D.; Tao, B.; Xiang, F.; Jiang, G.; Sun, Y.; Kong, J.; Li, G. A systematic review of digital twin about physical entities, virtual models, twin data, and applications. *Adv. Eng. Inform.* **2023**, *55*, 101876. [CrossRef]
3. Ramírez, M. Digital twins: The road to the transformation of the industrial sector. *Técnica Ind.* **2023**, *336*, 6–7. Available online: https://www.tecnicaindustrial.es/gemelos-digitales-el-camino-hacia-la-transformacion-del-sector-industrial/ (accessed on 17 February 2024).
4. Saracco, R. Digital Twins: Bridging Physical Space and Cyberspace. *Computer* **2019**, *52*, 58–64. [CrossRef]
5. Arnautova, Y. If You Build Products, You Should Be Using Digital Twins. [Online]. Available online: https://www.globallogic.com/insights/blogs/if-you-build-products-you-should-be-using-digital-twins/ (accessed on 18 February 2024).
6. El Bazi, N.; Mabrouki, M.; Laayati, O.; Ouhabi, N.; El Hadraoui, H.; Hammouch, F.E.; Chebak, A. Generic Multi-Layered Digital-Twin-Framework-Enabled Asset Lifecycle Management for the Sustainable Mining Industry. *Sustainability* **2023**, *4*, 3470. [CrossRef]
7. Conroy, M. Modeling, Simulation, Information Technology and Processing Roadmap. 2010. [Online]. Available online: https://www.researchgate.net/publication/280310295 (accessed on 10 February 2024).
8. Grieves, M. Digital Twin: Manufacturing Excellence through Virtual Factory Replication. [Online]. Available online: https://www.researchgate.net/publication/275211047 (accessed on 10 February 2024).
9. Wu, Y.; Zhou, L.; Zheng, P.; Sun, Y.; Zhang, K. A digital twin-based multidisciplinary collaborative design approach for complex engineering product development. *Adv. Eng. Inform.* **2022**, *52*, 101635. [CrossRef]
10. Liu, M.; Fang, S.; Dong, H.; Xu, C. Review of digital twin about concepts, technologies, and industrial applications. *J. Manuf. Syst.* **2021**, *58*, 346–361. [CrossRef]
11. Sepasgozar, S.M.E. Differentiating digital twin from digital shadow: Elucidating a paradigm shift to expedite a smart, sustainable built environment. *Buildings* **2021**, *11*, 151. [CrossRef]
12. Fuller, A.; Fan, Z.; Day, C.; Barlow, C. Digital Twin: Enabling Technologies, Challenges and Open Research. *IEEE Access* **2020**, *8*, 108952–108971. [CrossRef]
13. Sepasgozar, S.M.E. Digital twin and web-based virtual gaming technologies for online education: A case of construction management and engineering. *Appl. Sci.* **2020**, *10*, 4678. [CrossRef]
14. Errandonea, I.; Beltrán, S.; Arrizabalaga, S. Digital Twin for maintenance: A literature review. *Comput. Ind.* **2020**, *123*, 103316. [CrossRef]
15. Yu, G.; Zhang, S.; Hu, M.; Wang, Y.K. Prediction of highway tunnel tunnel pavement performance based on digital twin and multiple time series stacking. *Adv. Civil. Eng.* **2020**, *2020*, 8824135. [CrossRef]
16. Alam, K.M.; El Saddik, A. C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems. *IEEE Access* **2017**, *5*, 2050–2062. [CrossRef]
17. Mostafa, F.; Tao, L.; Yu, W. An effective architecture of digital twin system to support human decision making and AI-driven autonomy. In *Concurrency and Computation: Practice and Experience*; John Wiley and Sons Ltd.: Hoboken, NJ, USA, 2021. [CrossRef]
18. Onile, A.E.; Machlev, R.; Petlenkov, E.; Levron, Y.; Belikov, J. Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review. *Energy Rep.* **2021**, *7*, 997–1015. [CrossRef]
19. Stark, R.; Kind, S.; Neumeyer, S. Innovations in digital modelling for next generation manufacturing system design. *CIRP Ann Manuf Technol* **2017**, *66*, 169–172. [CrossRef]
20. Brosinsky, C.; Westermann, D.; Krebs, R. Recent and prospective developments in power system control centers: Adapting the digital twin technology for application in power system control centers. In Proceedings of the 2018 IEEE International Energy Conference (ENERGYCON), Limassol, Cyprus, 3–7 June 2018.
21. Lee, J.; Azamfar, M.; Singh, J.; Siahpour, S. Integration of digital twin and deep learning in cyber-physical systems: Towards smart manufacturing. *IET Collab. Intell. Manuf.* **2020**, *2*, 34–36. [CrossRef]

22. Yalçin, T.; Solà, P.P.; Stefanidou-Voziki, P.; Domínguez-García, J.L.; Demirdelen, T. Exploiting Digitalization of Solar PV Plants Using Machine Learning: Digital Twin Concept for Operation. *Energies* **2023**, *16*, 5044. [CrossRef]
23. Han'guk Chŏngbo Kwahakhoe; Institute of Electrical and Electronics Engineers; IEEE Computer Society; Denshi Jōhō Tsūshin Gakkai (Japan) Tsūshin Sosaieti; Han'guk T'ongsin Hakhoe. *The 34th International Conference on Information Networking (ICOIN 2020), Barcelona, Spain, 7–10 January 2020*; AC Hotel Barcelona Forum: Barcelona, Spain, 2020.
24. Castiglione, F.; Vergara, S.; Ramirez, G. Python software to monitor NCRE generation systems. In Proceedings of the 2021 IEEE CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies, CHILECON 2021, Valparaíso, Chile, 6–9 December 2021; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2021. [CrossRef]
25. Global IT Research Institute; IEEE Communications Society; Institute of Electrical and Electronics Engineers. *The 21st International Conference on Advanced Communications Technology: "ICT for 4th Industrial Revolution!": ICACT 2019, Phoenix Park, Pyeongchang, Republic of Korea, 17–20 February 2019*; IEEE: Piscataway, NJ, USA, 2019.
26. RVS Technical Campus; IEEE Electron Devices Society; Institute of Electrical and Electronics Engineers. *The Second International Conference on Electronics, Communication and Aerospace Technology (ICECA 2018), Coimbatore, India, 29–31 May 2018*; IEEE: Piscataway, NJ, USA, 2018.
27. Moghimi, M.; Bennett, C.; Leskarac, D.; Stegen, S.; Lu, J. Communication Architecture and Data Acquisition for Experimental MicroGrid Installations. In Proceedings of the 2015 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), Brisbane, QLD, Australia, 15–18 November 2015.
28. Ariesen-Verschuur, N.; Verdouw, C.; Tekinerdogan, B. Digital Twins in greenhouse horticulture: A review. *Comput. Electron. Agric.* **2022**, *199*, 107183. [CrossRef]
29. Kampker, A.; Stich, V.; Jussen, P.; Moser, B.; Kuntz, J. Business models for industrial smart services—The example of a digital twin for a product-service-system for potato harvesting. *Procedia CIRP* **2019**, *83*, 534–540. [CrossRef]
30. Verboven, P.; Defraeye, T.; Datta, A.K.; Nicolai, B. Digital twins of food process operations: The next step for food process models? *Curr. Opin. Food Sci.* **2020**, *35*, 79–87. [CrossRef]
31. OpenEMS Association, e.V. Open Energy Management System. [Online]. Available online: https://openems.github.io/openems.io/openems/latest/introduction.html (accessed on 10 June 2023).
32. Yuan, G.; Xie, F. Digital Twin-Based economic assessment of solar energy in smart microgrids using reinforcement learning technique. *Sol. Energy* **2023**, *250*, 398–408. [CrossRef]
33. Al-Isawi, O.A.; Amirah, L.H.; Al-Mufti, O.A.; Ghenai, C. Digital Twinning and LSTM-based Forecasting Model of Solar PV Power Output. In Proceedings of the 2023 Advances in Science and Engineering Technology International Conferences, ASET 2023, Dubai, United Arab Emirates, 21–24 February 2022; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2023. [CrossRef]
34. Xu, Y.; Sun, Y.; Liu, X.; Zheng, Y. A Digital-Twin-Assisted Fault Diagnosis Using Deep Transfer Learning. *IEEE Access* **2019**, *7*, 19990–19999. [CrossRef]
35. Jain, P.; Poon, J.; Singh, J.P.; Spanos, C.; Sanders, S.R.; Panda, S.K. A digital twin approach for fault diagnosis in distributed photovoltaic systems. *IEEE Trans. Power Electron.* **2020**, *35*, 940–956. [CrossRef]
36. Hong, Y.Y.; Pula, R.A. Diagnosis of PV faults using digital twin and convolutional mixer with LoRa notification system. *Energy Rep.* **2023**, *9*, 1963–1976. [CrossRef]
37. Wang, K.; Ma, J.; Wang, J.; Xu, B.; Tao, Y.; Man, K.L. Digital Twin based Maximum Power Point Estimation for Photovoltaic Systems. In Proceedings of the International SoC Design Conference 2022, ISOCC 2022, Gangneung-si, Republic of Korea, 19–22 October 2022; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2022; pp. 189–190. [CrossRef]
38. Artetxe, E.; Uralde, J.; Barambones, O.; Calvo, I.; Martin, I. Maximum Power Point Tracker Controller for Solar Photovoltaic Based on Reinforcement Learning Agent with a Digital Twin. *Mathematics* **2023**, *11*, 2166. [CrossRef]
39. Delussu, F.; Manzione, D.; Meo, R.; Ottino, G.; Asare, M. Experiments and Comparison of Digital Twinning of Photovoltaic Panels by Machine Learning Models and a Cyber-Physical Model in Modelica. *IEEE Trans. Ind. Inf.* **2022**, *18*, 4018–4028. [CrossRef]
40. Wang, Y.; Qi, Y.; Li, J.; Huan, L.; Li, Y.; Xie, B.; Wang, Y. The Wind and Photovoltaic Power Forecasting Method Based on Digital Twins. *Appl. Sci.* **2023**, *13*, 8374. [CrossRef]
41. Luis J., R.C.; José A., B.J.; Ian M., S.T.; Jesús H., M.L. Study of the Maximum Power Point Tracking Algorithm Perturb and Observe. *RIEE&C* **2010**, *8*, 17–23.
42. Femia, N.; Petrone, G.; Spagnuolo, G.; Vitelli, M. Optimizing Duty-cycle Perturbation of P&O MPPT Technique. In Proceedings of the 2004 IEEE 35th Annual Power Electronics Specialists Conference, Aachen, Germany, 20–25 June 2004.
43. Esram, T.; Chapman, P.L. Comparison of photovoltaic array maximum power point tracking techniques. *IEEE Trans. Energy Convers.* **2007**, *22*, 439–449. [CrossRef]
44. Esram, T.; Kimball, J.W.; Krein, P.T.; Chapman, P.L.; Midya, P. Dynamic maximum power point tracking of photovoltaic arrays using ripple correlation control. *IEEE Trans. Power Electron.* **2006**, *21*, 1282–1290. [CrossRef]
45. Kouta, J.; El-Ali, A.; Moubayed, N.; Outbib, R. Improving the incremental conductance control method of a solar energy conversion system. *Renew. Energy Power Qual. J.* **2008**, *1*, 273–276. [CrossRef]
46. Femia, N.; Petrone, G.; Spagnuolo, G.; Vitelli, M. Optimization of perturb and observe maximum power point tracking method. *IEEE Trans. Power Electron.* **2005**, *20*, 963–973. [CrossRef]

47. Ko, J.S.; Huh, J.H.; Kim, J.C. Overview of maximum power point tracking methods for PV system in micro grid. *Electronics* **2020**, *9*, 816. [CrossRef]
48. Ahmed, J.; Salam, Z. An Enhanced Adaptive P&O MPPT for Fast and Efficient Tracking Under Varying Environmental Conditions. *IEEE Trans. Sustain. Energy* **2018**, *9*, 1487–1496. [CrossRef]
49. Macaulay, J.; Zhou, Z. A fuzzy logical-based variable step size P&O MPPT algorithm for photovoltaic system. *Energies* **2018**, *11*, 1340. [CrossRef]
50. Farhat, M.; Barambones, O.; Sbita, L. A real-time implementation of novel and stable variable step size MPPT. *Energies* **2020**, *13*, 4668. [CrossRef]
51. Mendez, E.; Ortiz, A.; Ponce, P.; Macias, I.; Balderas, D.; Molina, A. Improved MPPT algorithm for photovoltaic systems based on the earthquake optimization algorithm. *Energies* **2020**, *13*, 3047. [CrossRef]
52. Ajani, T.S.; Imoize, A.L.; Atayero, A.A. An overview of machine learning within embedded and mobile devices-optimizations and applications. *Sensors* **2021**, *21*, 4412. [CrossRef] [PubMed]
53. Li, C.; Chen, Y.; Zhou, D.; Liu, J.; Zeng, J. A high-performance adaptive incremental conductance MPPT algorithm for photovoltaic systems. *Energies* **2016**, *9*, 288. [CrossRef]
54. Kofinas, P.; Doltsinis, S.; Dounis, A.I.; Vouros, G.A. A reinforcement learning approach for MPPT control method of photovoltaic sources. *Renew. Energy* **2017**, *108*, 461–473. [CrossRef]
55. Chou, K.Y.; Yang, S.T.; Chen, Y.P. Maximum power point tracking of photovoltaic system based on reinforcement learning. *Sensors* **2019**, *19*, 5054. [CrossRef] [PubMed]
56. Phan, B.C.; Lai, Y.C.; Lin, C.E. A deep reinforcement learning-based MPPT control for PV systems under partial shading condition. *Sensors* **2020**, *20*, 3039. [CrossRef] [PubMed]
57. Nicola, M.; Nicola, C.I.; Selișteanu, D. Improvement of the Control of a Grid Connected Photovoltaic System Based on Synergetic and Sliding Mode Controllers Using a Reinforcement Learning Deep Deterministic Policy Gradient Agent. *Energies* **2022**, *15*, 2392. [CrossRef]
58. Humada, A.M.; Hojabri, M.; Mekhilef, S.; Hamada, H.M. Solar cell parameters extraction based on single and double-diode models: A review. *Renew. Sustain. Energy Rev.* **2016**, *56*, 494–509. [CrossRef]
59. Wang, K.; Ma, J.; Man, K.L.; Huang, K.; Huang, X. Sim-to-Real Transfer with Domain Randomization for Maximum Power Point Estimation of Photovoltaic Systems. In Proceedings of the 21st IEEE International Conference on Environment and Electrical Engineering and 2021 5th IEEE Industrial and Commercial Power System Europe, EEEIC/I and CPS Europe 2021, Bari, Italy, 7–10 September 2021; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2021. [CrossRef]
60. Wang, K.; Ma, J.; Man, K.L.; Hong, D.; Huang, K.; Huang, X. Real-time Modeling of Photovoltaic Strings under Partial Shading Conditions. In Proceedings of the 2021 IEEE 10th Data Driven Control and Learning Systems Conference, DDCLS 2021, Suzhou, China, 14–16 May 2021; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2021; pp. 1345–1349. [CrossRef]
61. Lillicrap, T.P.; Hunt, J.J.; Pritzel, A.; Heess, N. Continuous Control with Deep Reinforcement Learning. 2015. [Online]. Available online: https://www.researchgate.net/publication/281670459 (accessed on 5 January 2024).
62. Raj, A.; Gupta, M. Numerical Simulation and Performance Assessment of ANN-INC Improved Maximum Power Point Tracking System for Solar Photovoltaic System Under Changing Irradiation Operation. 2021. [Online]. Available online: http://annalsofrscb.ro790 (accessed on 5 January 2024).
63. Fang, X.; Misra, S.; Xue, G.; Yang, D. Smart grid—The new and improved power grid: A survey. *IEEE Commun. Surv. Tutor.* **2012**, *14*, 944–980. [CrossRef]
64. Pombo, D.V.; Bacher, P.; Ziras, C.; Bindner, H.W.; Spataru, S.V.; Sørensen, P.E. Benchmarking physics-informed machine learning-based short term PV-power forecasting tools. *Energy Rep.* **2022**, *8*, 6512–6520. [CrossRef]
65. Cordeiro-Costas, M.; Villanueva, D.; Eguía-Oller, P.; Granada-Álvarez, E. Machine Learning and Deep Learning Models Applied to Photovoltaic Production Forecasting. *Appl. Sci.* **2022**, *12*, 8769. [CrossRef]
66. Muzaffar, S.; Afshari, A. Short-term load forecasts using LSTM networks. *Energy Procedia* **2019**, *158*, 2922–2927. [CrossRef]
67. Choi, H.; Ryu, S.; Kim, H. Short-Term Load Forecasting based on ResNet and LSTM. In Proceedings of the 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids, SmartGridComm 2018, Aalborg, Denmark, 29–31 October 2018; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2018. [CrossRef]
68. Tian, Y.; Wang, D.; Zhou, G.; Wang, J.; Zhao, S.; Ni, Y. An Adaptive Hybrid Model for Wind Power Prediction Based on the IVMD-FE-Ad-Informer. *Entropy* **2023**, *25*, 647. [CrossRef]
69. Poczeta, K.; Papageorgiou, E.I. Energy Use Forecasting with the Use of a Nested Structure Based on Fuzzy Cognitive Maps and Artificial Neural Networks. *Energies* **2022**, *15*, 7542. [CrossRef]
70. Dranka, G.G.; Ferreira, P.; Vaz, A.I.F. Integrating supply and demand-side management in renewable-based energy systems. *Energy* **2021**, *232*, 120978. [CrossRef]
71. Dabbaghjamanesh, M.; Moeini, A.; Kavousi-Fard, A. Reinforcement Learning-Based Load Forecasting of Electric Vehicle Charging Station Using Q-Learning Technique. *IEEE Trans. Ind. Inf.* **2021**, *17*, 4229–4237. [CrossRef]
72. Chen, H.; Li, Y.; Louie, R.H.Y.; Vucetic, B. Autonomous demand side management based on energy consumption scheduling and instantaneous load billing: An aggregative game approach. *IEEE Trans. Smart Grid* **2014**, *5*, 1744–1754. [CrossRef]

73. Ma, T.; Pei, W.; Xiao, H.; Kong, L.; Mu, Y.; Pu, T. The energy management strategies based on dynamic energy pricing for community integrated energy system considering the interactions between suppliers and users. *Energy* **2020**, *211*, 118677. [CrossRef]
74. Veras, J.M.; Silva, I.R.S.; Pinheiro, P.R.; Rabêlo, R.A.L.; Veloso, A.F.S.; Borges, F.A.S.; Rodrigues, J.J.P.C. A multi-objective demand response optimization model for scheduling loads in a home energy management system. *Sensors* **2018**, *18*, 3207. [CrossRef] [PubMed]
75. Lu, Q.; Lü, S.; Leng, Y.; Zhang, Z. Optimal household energy management based on smart residential energy hub considering uncertain behaviors. *Energy* **2020**, *195*, 117052. [CrossRef]
76. Li, W.; Cheng, D.; Bian, R.; Ishak, S.; Osman, O.A. Accounting for travel time reliability, trip purpose and departure time choice in an agent-based dynamic toll pricing approach. *IET Intell. Trans. Syst.* **2018**, *12*, 58–65. [CrossRef]
77. Bellinguer, K.; Girard, R.; Bontron, G.; Kariniotakis, G. A generic methodology to efficiently integrate weather information in short-term Photovoltaic generation forecasting models. *Sol. Energy* **2022**, *244*, 401–413. [CrossRef]
78. Güngör, O.; Akşanlı, B.; Aydoğan, R. Algorithm selection and combining multiple learners for residential energy prediction. *Future Gener. Comput. Syst.* **2019**, *99*, 391–400. [CrossRef]
79. Nasyrov, R.; Ţulbah, M.F. Moscow Power Engineering Institute, IEEE Industry Applications Society, and Institute of Electrical and Electronics Engineers. In Proceedings of the 2nd 2020 International Youth Conference on Radio Electronics, Electrical and Power Engineering (REEPE), Moscow, Russia, 12–14 March 2020.
80. Goel, V.; Weng, J.; Poupart, P. Unsupervised Video Object Segmentation for Deep Reinforcement Learning. *arXiv* **2018**, arXiv:1805.07780.
81. Zhu, L.; Huang, K.; Hu, Y.; Tai, X. A Self-Adapting Task Scheduling Algorithm for Container Cloud Using Learning Automata. *IEEE Access* **2021**, *9*, 81236–81252. [CrossRef]
82. Chand Bansal, J.; Deep, K.; Nagar, A.K. *Applications of Artificial Intelligence in Engineering, Proceedings of First Global Conference on Artificial Intelligence and Applications (GCAIA 2020)*; Algorithms for Intelligent Systems Series Editors; Springer: Singapore, 2021; [Online]. Available online: http://www.springer.com/series/16171 (accessed on 5 January 2024).
83. Bazzi, A.M.; Kim, K.A.; Johnson, B.B.; Krein, P.T.; Dominguez-García, A. Fault impacts on solar power unit reliability. In Proceedings of the IEEE Applied Power Electronics Conference and Exposition—APEC 2011, Fort Worth, TX, USA, 6–10 March 2011; pp. 1223–1231. [CrossRef]
84. Köntges, M. *Assessment of Photovoltaic Module Failures in the Field*; International Energy Agency: Paris, France, 2017.
85. Jamshidpour, E.; Poure, P.; Saadate, S. Photovoltaic Systems Reliability Improvement by Real-Time FPGA-Based Switch Failure Diagnosis and Fault-Tolerant DC-DC Converter. *IEEE Trans. Ind. Electron.* **2015**, *62*, 7247–7255. [CrossRef]
86. Poon, J.; Jain, P.; Konstantakopoulos, I.C.; Spanos, C.; Panda, S.K.; Sanders, S.R. Model-based fault detection and identification for switching power converters. *IEEE Trans. Power Electron.* **2017**, *32*, 1419–1430. [CrossRef]
87. Kim, K.A.; Seo, G.S.; Cho, B.H.; Krein, P.T. Photovoltaic Hot-Spot Detection for Solar Panel Substrings Using AC Parameter Characterization. *IEEE Trans. Power Electron.* **2016**, *31*, 1121–1130. [CrossRef]
88. Yang, S.; Xiang, D.; Bryant, A.; Mawby, P.; Ran, L.; Tavner, P. Condition monitoring for device reliability in power electronic converters: A review. *IEEE Trans. Power Electron.* **2010**, *25*, 2734–2752. [CrossRef]
89. Wang, H.; Liserre, M.; Blaabjerg, F.; Rimmen, P.d.P.; Jacobsen, J.B.; Kvisgaard, T.; Landkildehus, J. Transitioning to physics-of-failure as a reliability driver in power electronics. *IEEE J. Emerg. Sel. Top Power Electron.* **2014**, *2*, 97–114. [CrossRef]
90. Mellit, A.; Tina, G.M.; Kalogirou, S.A. Fault detection and diagnosis methods for photovoltaic systems: A review. *Renew. Sustain. Energy Rev.* **2018**, *91*, 1–17. [CrossRef]
91. Mellit, A.; Kalogirou, S. Artificial intelligence and internet of things to improve efficacy of diagnosis and remote sensing of solar photovoltaic systems: Challenges, recommendations and future directions. *Renew. Sustain. Energy Rev.* **2021**, *143*, 110889. [CrossRef]
92. Pillai, D.S.; Rajasekar, N. A comprehensive review on protection challenges and fault diagnosis in PV systems. *Renew. Sustain. Energy Rev.* **2018**, *91*, 18–40. [CrossRef]
93. Zheng, Y.; Yang, S.; Cheng, H. An application framework of digital twin and its case study. *J. Ambient. Intell. Humaniz. Comput.* **2019**, *10*, 1141–1153. [CrossRef]
94. Nguyen, V.H.; Tran, Q.T.; Besanger, Y.; Jung, M.; Nguyen, T.L. Digital twin integrated power-hardware-in-the-loop for the assessment of distributed renewable energy resources. *Electr. Eng.* **2022**, *104*, 377–388. [CrossRef]
95. Kasper, M.; Bortis, D.; Kolar, J.W. Classification and comparative evaluation of PV panel-integrated DC-DC converter concepts. *IEEE Trans. Power Electron.* **2014**, *29*, 2511–2526. [CrossRef]
96. Perpiñan, O.; Lorenzo, E.; Castro, M.A. On the calculation of energy produced by a PV grid-connected system. *Prog. Photovolt. Res. Appl.* **2007**, *15*, 265–274. [CrossRef]
97. Linares, L.; Erickson, R.W.; Macalpine, S.; Brandemuehl, M. Improved Energy Capture in Series String Photovoltaics via Smart Distributed Power Electronics. In Proceedings of the 2009 Twenty-Fourth Annual IEEE Applied Power Electronics Conference and Exposition, Washington, DC, USA, 15–19 February 2009.
98. Karimi, S.; Gaillard, A.; Poure, P.; Saadate, S. FPGA-based real-time power converter failure diagnosis for wind energy conversion systems. *IEEE Trans. Ind. Electron.* **2008**, *55*, 4299–4308. [CrossRef]

99. Youssef, A.B.; El Khil, S.K.; Slama-Belkhodja, I. State observer-based sensor fault detection and isolation, and fault tolerant control of a single-phase PWM rectifier for electric railway traction. *IEEE Trans. Power Electron.* **2013**, *28*, 5842–5853. [CrossRef]
100. Solórzano, J.; Egido, M.A. Automatic fault diagnosis in PV systems with distributed MPPT. *Energy Convers. Manag.* **2013**, *76*, 925–934. [CrossRef]
101. Nie, S.; Pei, X.; Chen, Y.; Kang, Y. Fault diagnosis of PWM DC-DC converters based on magnetic component voltages equation. *IEEE Trans. Power Electron.* **2014**, *29*, 4978–4998. [CrossRef]