# Microgrid Digital Twins: Concepts, Applications, and Future Trends

**NAJMEH BAZMOHAMMADI[1], (Member, IEEE), AHMAD MADARY[2],
JUAN C. VASQUEZ[1], (Senior Member, IEEE), HAMID BAZ MOHAMMADI[3],
BASEEM KHAN[4], (Senior Member, IEEE), YING WU[1],
AND JOSEP M. GUERRERO[1], (Fellow, IEEE)**

[1]Center for Research on Microgrids (CROM), AAU Energy, Aalborg University, 9220 Aalborg, Denmark
[2]Mechanical and Production Engineering Department, Aarhus University, 8000 Aarhus, Denmark
[3]Radio Access Performance Engineering Department, TELUS, Calgary, AB T2A 4Y2, Canada
[4]Department of Electrical and Computer Engineering, Hawassa University, Hawassa 05, Ethiopia

Corresponding authors: Josep M. Guerrero (joz@et.aau.dk) and Baseem Khan (baseemkh@hu.edu.et)

**ABSTRACT** Following the fourth industrial revolution, and with the recent advances in information and communication technologies, the *digital twinning* concept is attracting the attention of both academia and industry worldwide. A microgrid digital twin (MGDT) refers to the digital representation of a microgrid (MG), which mirrors the behavior of its physical counterpart by using high-fidelity models and simulation platforms as well as real-time bi-directional data exchange with the real twin. With the massive deployment of sensor networks and IoT technologies in MGs, a huge volume of data is continuously generated, which contains valuable information to enhance the performance of MGs. MGDTs provide a powerful tool to manage the huge historical data and real-time data stream in an efficient and secure manner and support MGs' operation by assisting in their design, operation management, and maintenance. In this paper, the concept of the digital twin (DT) and its key characteristics are introduced. Moreover, a workflow for establishing MGDTs is presented. The goal is to explore different applications of DTs in MGs, namely in design, control, operator training, forecasting, fault diagnosis, expansion planning, and policy-making. Besides, an up-to-date overview of studies that applied the DT concept to power systems and specifically MGs is provided. Considering the significance of situational awareness, security, and resilient operation for MGs, their potential enhancement in light of digital twinning is thoroughly analyzed and a conceptual model for resilient operation management of MGs is presented. Finally, future trends in MGDTs are discussed.

**INDEX TERMS** Artificial intelligence, automatic learning, big data, decision support system, digital twin, Industry 4.0, microgrids.

## I. INTRODUCTION

In recent years, with the advances in information and communication technologies, digitalization and automation have been profoundly influencing different industries. Major advances in the internet of things (IoT), cyber-physical-systemss (CPSs), artificial intelligence (AI), and big data analytics (BDA) are the main drivers of this revolution [1]–[3]. According to the industrial revolution paradigm or Industry 4.0, the next-generation systems are the outcome of

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the evolution and convergence of new technologies such as onboard computation, intelligent and fast controllers, big data analytic, machine learning (ML), and IoT technologies [4]. With these advances, the real-time data streams can be continuously gathered, processed, and analyzed along with the high-fidelity models to create a digital representation of a complex system and provide a great insight into its current and future operating status. Thus, a precise, up-to-date, and dynamic virtual representation of the system is available for real-time supervisory and control. This concept is known as *digital twinning* and is increasingly receiving the attention of academia and industry across sectors.

Broadly, digital twins (DTs) are defined as *software-based abstractions of complex physical systems that are connected to the real system via a communication link to continuously exchange data with the real environment and establish a dynamic digital mirror with a constantly running modeling engine* [1]. The original idea of creating a twin for a system formed in NASA's Apollo program in which to mirror the conditions of the main vehicle in space, another vehicle identical to the main one was built on earth and called the twin. The term DT was then introduced in 2012 in NASA's integrated technology road map under Technology area 11, where DT was defined as *An integrated multi-physics, multi-scale simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, and so on, to mirror the life of its corresponding flying twin,* [5], [6]. Besides, the DT concept was proposed from the perspective of product life cycle management by Dr. Grieves in 2003 and later on in a white paper in 2014 [7]. In the aviation industry, the twinning approach has been adopted a long-time ago to train the operators in similar real flight situations.

Although the birthplace of twinning is in aerospace and aviation industries, it rapidly found its applications in manufacturing [2], [8]–[10], petrochemical [11], [12], and automotive systems [13], [14], urbanization and smart cities [15], [16], healthcare system [17] for elderly healthcare services [18] and remote surgery [19], and power system industry [1], [20], [21]. A review of the industrial applications of DT can be found in [22]. In [23], DT is introduced as a key aspect of smart manufacturing systems besides the three other aspects of modularity, connectivity, and autonomy. In [11], a ML-driven DT is developed for production optimization in the petrochemical industry. The model is trained using the data collected from the petrochemical industrial IoT systems, business transaction driven systems, and data mapping based on knowledge in business models. In [15], the smart city DT is introduced as a tool for studying the dynamics governing the complex interdependency between humans, infrastructures, and technology and understanding cities' response to changes through implementing what-if scenarios.

In [24], DT is defined as *a set of virtual information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level. At its optimum, any information that could be inspected from a physical product can be obtained from its DT* [24]–[26]. In [27], DT is characterized by the ability to simulate the systems in different scales of time relying on *expert knowledge and field experience aggregating through data collection*. Digital twinning has been also attracting the attention of power system society during the last years. In [28], DT is defined as *the virtual image of the physical object in the electrical power system, which makes the provided data usable for various purposes in the control center*. The differences between DT and power system simulation, power system online analysis, and CPSs are described in [20]. The key difference between DT and other simulation or representation methods is that DT is dynamic and intelligent by design.

Through establishing a bi-directional relation between the digital and physical systems, the performance of both systems can be continuously improved. The real-time data stream will help to improve the twinning accuracy autonomously and dynamically while a DT-driven decision support system (DSS) can assist system operators to improve the physical system performance [29].

From simulation perspective, DT is the next simulation paradigm [30] as represented in Fig. 1 adapted from [30]. With the advent of DT, the utilization of the simulation model is expanded over the entire lifetime of the system/process [30]. An accurate and dynamic representation of a microgrid (MG) is beneficial during the MGs whole life cycle from planning phase to operation, maintenance, and expanding stages. Having the microgrid digital twin (MGDT) before MGs construction will provide the designers with the opportunity of optimizing their design and analyzing the consequences of their decisions in a low-cost low-risk environment. Thus, with deploying MGDT concept, a closed-loop can be formed from operation and maintenance back to the design and development of MGs [6].

Taking the promising advantages of digital twinning, different companies started adopting DT in their solution strategies. General Electric (GE), Siemens, ABB, and Rolls-Royce are among the pioneers in this area. A DT interface for managing wind farms has been developed by GE [31] including the topography and environmental information of the wind farms. Siemens has started to develop a digital grid model-ELVIS- for the Finland transmission system in 2016. The digital model supports asset management, operation management, investment planning, and forecasting of future energy consumption [32]. In addition, American electric power (AEP) transmission initiated a collaboration with Siemens in 2017 to develop a DT-based solution for better coordination of network model information across different domains and to centralize management of the information. This way, the time and cost caused by manual coordination will be reduced [32]. Siemens is also among the early adopters of digitalization and industrial edge technology in drive systems [33]. In marine systems, ABB is among the DT adopters for remote monitoring and predictive maintenance purposes. According to [34], the ABB marine remote diagnostic system for monitoring and predictive maintenance has considerably reduced their onboard visits. Rolls-Royce Marine has also established a collaboration with a number of leading maritime players to develop an open simulation platform for creating DTs of existing and future vessels [35].

This paper aims to introduce the concept of MGDT and present different steps of establishing a DT for MGs. Besides, different services that can be provided by MGDTs during the MGs' lifetime are explored. Moreover, related state-of-the-art studies that applied the DT concept to power system applications and specifically MGs are reviewed.

The remainder of this paper is organised as follows. Establishing MGDTs is presented in Section II. In Section III, DT applications in MGs including MGs design, control and
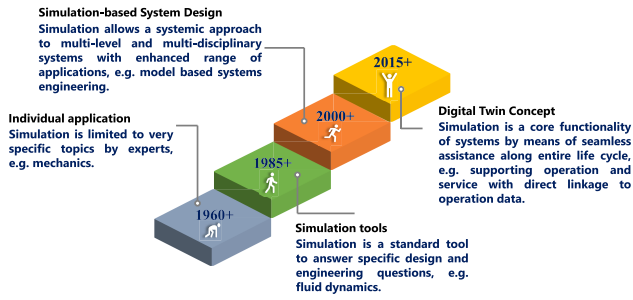
**FIGURE 1.** Digital twin: the new simulation paradigm [30].

operation management, operator training, forecasting, state of health (SoH) monitoring and predictive maintenance, fault diagnosis, security, resiliency, and situational awareness and expansion planning are discussed. Future trends of MGDTs are discussed in Section IV. Finally, the paper is concluded in Section V.

## II. ESTABLISHING A DIGITAL TWIN FOR MICROGRIDS

The digital twinning framework consists of three parts, physical system, virtual system, and the data exchange between these two systems. To build a DT, high-fidelity models are integrated with the available multi-source data such as sensor data, historical data, technical information, maintenance history, and so on [29]. The data is used to develop models of the physical system and preserve the models' accuracy under different operating conditions. Thus, very realistic and up-to-date perception of the state of operation of the system is available for reasoning and decision-making purposes. In the following, different steps of establishing DTs will be introduced (see Fig. 2).
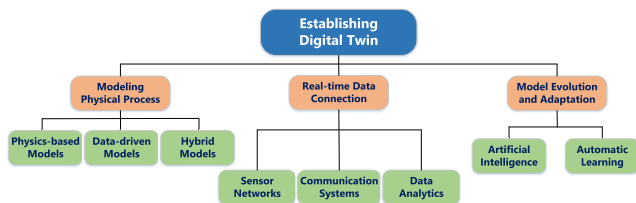


**FIGURE 2.** Establishing a digital twin.

### A. MODELING OF PHYSICAL SYSTEMS AND PROCESSES

Modeling forms the basis of digital twinning [22]. The first step in establishing a DT is building accurate models of the real system or asset, which can mirror the behavior of the real twin. To establish the virtual model, the best available knowledge of the system dynamics should be used and integrated with the available data. The data includes the historical data obtained from the system under various operating conditions. The complete model of a system is achieved by integrating models of all subsystems and their interactions [36].

For modeling purposes, physics-based, data-driven, and hybridization of both can be used. Physics-based models are based on the first principle physical models and the exact

mathematical models of the system dynamics that explain the system behavior. In case there is a lack of knowledge about some parameters, the model is *adaptively* identified based on the most recently obtained data reflecting the current operating condition of the system. Heuristic techniques and AI methods are widely used for parameter identification. This approach is used in [37] to model a buck converter. In [38], artificial neural network (ANN) is used to tune the parameters of an inverter model.

Data-driven models can account for different phenomena which are usually very hard to formulate mathematically. They can also take into account the long-term historical data that is very challenging to do in physics-based modeling [39]. However, huge data of the system in various operating conditions are required to train the models using advanced ML techniques. Besides, the model might generalize poorly in unseen operating conditions and the accuracy might degrade over time. Therefore, it is important that data-driven models are continuously enriched with real-time data to embrace the current state of the behavior of the system, to enhance the model accuracy, and keep it as matched as possible to the real counterpart.

Taking the advantages of both physics-based and data-driven models, hybridization of both approaches is considered as a promising modeling solution for digital twinning purposes. Constructing of DTs from a modeling point of view is discussed in detail in [39].

It is worth noticing that a central aspect of the DT is the ability to provide different information in a consistent format [26]. Taking into account the purpose of deploying DT and the intended application, various models with different levels of abstractions could be developed. While complex models feature higher accuracy, the computational time for assessing the model will be the main barrier. Thus, in case a system-level analysis is required, approximate reduced order models with less complexity are highly preferred. For instance, considering the hierarchical control of MGs [40], the exact dynamics of different components is not needed at the tertiary level known as energy management system (EMS). In this case, having the information of energy flows among various subsystems and the approximate input-output power relation of different components is enough to guarantee the power balance at the system level. Besides, the model provides the required information to evaluate the key performance indicatorss (KPIs) such as the operating cost, emission, reliability, and system losses among others. As an example, simplified models of the MG's components such as photo voltaic (PV) systems (equivalent circuit models or black-box models) accompanied with the field meteorological data suffice for the short-term prediction of their available power [41]. On the other hand, for studying the degradation of PV cells, a detailed analysis of microscopic performance limiters is needed [42]. It is worth mentioning that the inter-operability of different services and sharing models and data in an efficient and secure manner are among the key functionalities of DTs.

All the models are continuously updated and synchronized to make sure that the DT closely tracks the behavior of the physical system and there is no inconsistency between different models. In this sense, *twinning rate* refers to the rate at which the DT is updated based on the most recent information of the physical system. After developing the DT models, their fidelity should be carefully validated to ensure reflecting the behavior of the physical twin before starting to use them.

### B. REAL-TIME DATA CONNECTION

Digital twinning relies on data for interlinking the digital models with their physical counterparts. Data is gathered through field measurements, IoT devices, and smart meters from different system components, lines, buses, switches, transformers, loads, storage systems, and so on. Besides, the meteorological information such as the ambient temperature, solar radiation, humidity, wind speed, and wind direction are collected from the field or other data centers such as a national/local weather station, adjacent interconnected systems, etc. However, handling a huge volume of data including structured, unstructured, and semi-structured data received from multiple resources with different resolutions is a challenging task.

After collecting the data, advanced data analysis techniques are required to pre-process the noisy raw data and enhance data quality. The relevant data is used to extract the information required to update the models of different parts of the system/process and share them with the unit/service in need of it.

Data is transferred through reliable and secure communication systems. Identification of suitable communication technologies is performed according to the communication requirements of the target service and application. These requirements can be classified into quantitative requirements such as *latency*, *reliability*, *coverage*, *data rate*, and *cost* as well as qualitative requirements including *scalability*, *interoperability*, *flexibility*, and *security* [43]. In this regard, different wired communication technologies, WiFi, WiMAX, 4G/5G, and satellite technologies or a hybrid communication system can be considered for different purposes in DTs. A detailed review of different communication technologies and their specifications can be found in [43].

Fig. 3 presents the schematic view of a monitoring system for real-time data collection of outdoor meteorological parameters and renewable power production of a prosumer including measuring devices, data acquisition system, communication system, and servers. The weather station comprises an anemometer including both wind speed and wind direction sensors, temperature and humidity sensors, a solar radiation sensor, a UV radiation sensor, a pressure sensor, and a rain sensor. Specifications of sensors are given in Table 1. Besides, the prosumer meter is used to measure real-time power production of the wind turbine (WT) and PV system. Data is collected and transferred to be stored in the server for further usage and analysis. As data is collected

**TABLE 1.** List of weather station sensors to measure meteorological parameters [45].

| Sensor | Measured parameter | Range | Update Interval [sec] |
|---|---|---|---|
| Wind speed sensor | Wind speed | 0 to 89 $m/s$ | 2.5 − 3 |
| Wind direction sensor | Wind direction | 0 to 360° | 2.5 − 3 |
| Solar radiation sensor | Solar radiation intensity | 0 to 1800 $W/m^2$ | 50 − 60 (5 min when dark) |
| UV radiation sensor | UV Dose | 0 to 199 $MEDs$ | 50 − 60 (5 min when dark) |
| Temperature sensor | Outside temperature | −40°C to 65°C | 10-12 |
| Relative humidity sensor | Outside relative humidity | 1 to 100%$RH$ | 50-60 |
| Rain sensor | Rain fall Rain rate | 0 to 999.8 $mm$ 0 to 762 $mm/hr$ | 20-24 |
| Pressure sensor | Barometric pressure | 410 to 820 $mmHg$ | 60 |

from different sensors with different frequencies, unification, alignment, and pre-processing of the raw data is of vital importance to prepare the data for its intended application such as WT and PV system monitoring and control, demand-side management, EMS, etc. Interested readers are referred to [44] for more information.
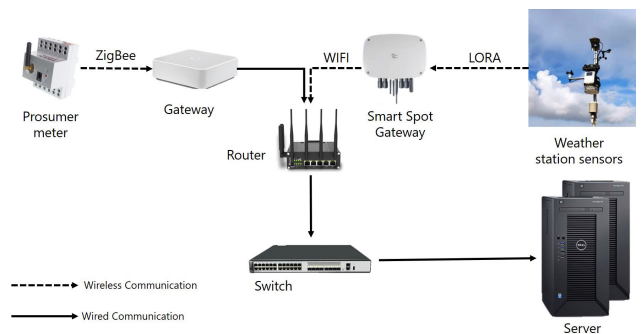


**FIGURE 3.** Schematic view of an exemplary monitoring system.

Real-time managing of a MGDT to keep it updated and synchronized with the physical system is of vital importance. Besides, the potential of MGDT to improve the situational awareness (SA) of the system relies on the fast and efficient processing of the large volume of real-time data for timely detection of events before the system reaches critical conditions or goes under a cascading catastrophe.

With recent advances in BDA, massive data could be processed to extract valuable information from the raw data. As a result, BDA plays an important role in digital twinning.

Thanks to the computing power and huge storage capabilities of cloud computing, BDAs could be employed in the digital twinning process for *bad data filtration*, *dimension reduction*, *data fusion*, *data organization*, *data mining*, *processing*, and *visualization* [46]. Many big data-driven
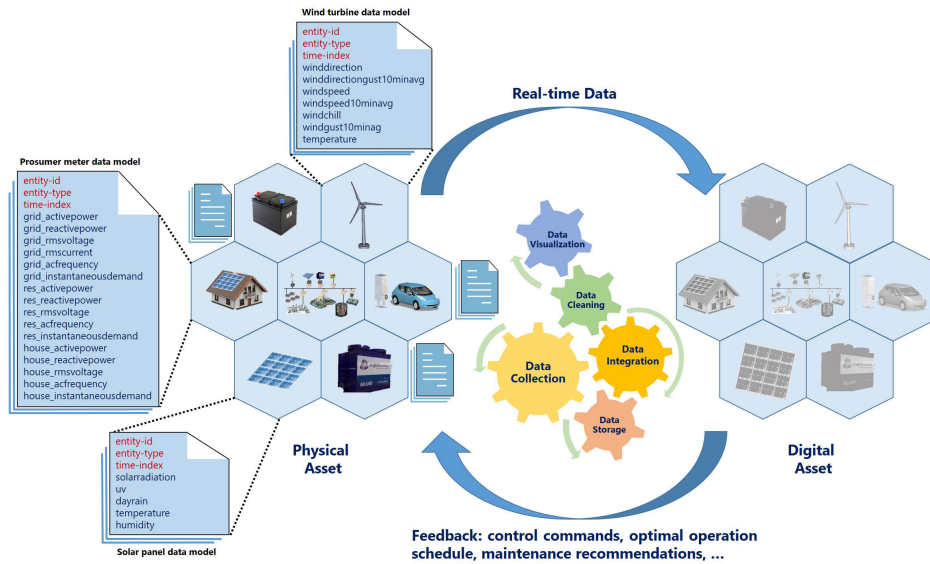
**FIGURE 4.** Physical system, digital system, and data exchange between them.

approaches have been proposed for different purposes in smart grids over the recent years [46], [47]. In [48], cloud-based BDA is used for the integration of discrete and continuous technical and business data streams of wind farms. The data visualization is done by using augmented reality (AR) for wind farm monitoring and analysis.

Taking into account the sensitivity of the application to the data transition latency and the level of integration of MGDT-driven services (device-level, system-level, and so on), edge, fog, and cloud computing platforms can be used. In this way, real-time data connection and analysis can be implemented at the desired level to support the data requirement of the target service. For instance, embedded DT-based controllers operation can be supported by employing device-level data analysis to facilitate their prompt and decisive response.

A recent survey of deploying AI techniques at the network edge and the proximity of the data source can be found in [49]. Fig. 4 represents the interrelationship between the physical system (process and components) of a MG and its DT, and the data exchange between these two systems. Data models represent an example of data that is gathered from the components and transmitted to the MGDT.

### C. DEVELOPING SYSTEMATIC WAYS TO MODEL ADAPTATION

DT is a living model of a physical system, thereby preserving the models' accuracy and consistency is of paramount importance. However, this is a challenging task as the physical system operating conditions and the environment are exposed to continuous changes over time. For instance, in a MG, power consumption patterns of a region can change due to several reasons such as changes in social and economic circumstances, changing weather conditions, emergence of new technologies and home appliances that can result in

divergence between the modeled output and the actual output of the system. In this regard, continuous updating of the models are among the main challenges of establishing a DT for different systems/processes. Based on the real-time data stream continuously collected through monitoring systems and processed by data analysis methods, models are updated throughout the systems' lifetime.

Model adaptation can be implemented by tuning model parameters/hyperparameters, engineering more features (in case of using data-driven models) or optimizing the physical principles used for building the models [50] (in case of deploying physics-based models). Besides, different trigger strategies can be followed for model adaptation. Models can be updated with a fixed periodicity that is defined based on the observed changes in the historical data and experts' knowledge of the system. Another more efficient strategy is an event-based approach in which triggers are defined based on the level of divergence between the model predictions and the physical system outputs. The trigger event could also be defined based on the drastic changes in the input data. The model adaptation process will be triggered in case critical boundaries are violated over a certain number of periods as shown in Fig. 5. In this figure, each vertical line is a measurement point. The retraining counter triggers when the gap between the actual values and the model output (predicted values) is greater than the configured maximum error tolerance and resets to zero if the maximum tolerance is not crossed. Once the counter reaches a predefined tolerance *n*, the retraining process is triggered. A general framework for model adaptation is presented in Fig. 6. Regarding the model selection in this figure, a model can be selected from a pool of candidate models in a systematic process to best fit the available data. The solution might be also to ensemble the output of different models to reach the best performance.
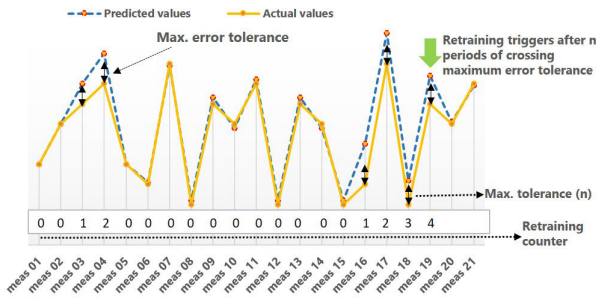
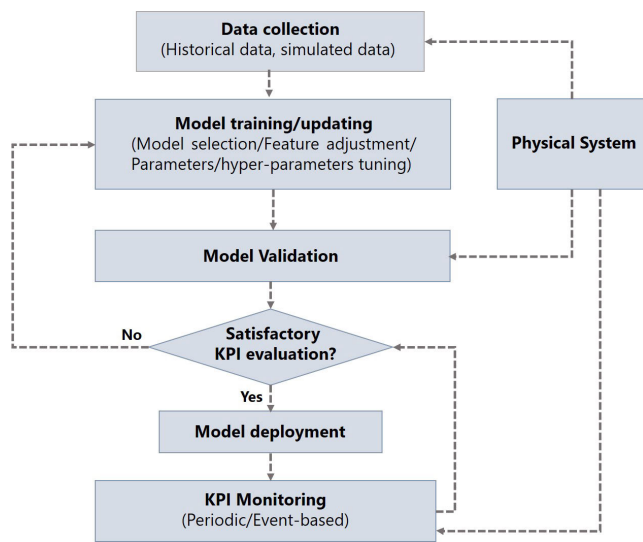**FIGURE 5.** An example of model drift and triggering model updating process.



**FIGURE 6.** A general flowchart for model adaptation.



**FIGURE 7.** DT modelling engine main functionalities.

The increase of models' complexity and the high rate of data arrival complicate the model adaptation task and call for automating the process. Hence, built-in systematic ways for automatic ingestion of real-time data and fast response to model update triggers should be developed for DTs. Model adaptation triggers should be defined in association with DT-based services requirements and the fixed/time-varying twinning rate. With the recent advancements in online and incremental learning with ML algorithms and reinforcement learning, efficient techniques can be developed for model adaptation purposes. A review on continual lifelong learning can be found in [51]. Statistical approaches using Bayesian techniques have been also used for model updating integration [52]. In this approach, the posterior distribution of model parameters is used as the new prior for updating the knowledge of unknown system parameters based on the new incoming data.

It is worth noticing that the MGDT is required to be shared with different MG services with a variety of requirements. In this sense, sharing the required virtual models with the desired level of abstraction and preserving the consistency of different models are crucial. To share data and inter-communication of DT-based services, efficient and secure application programming interfaces (APIs) are required to be deployed.
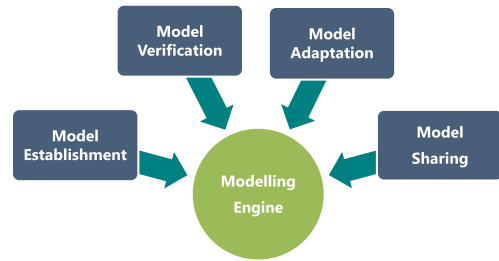
As a conclusion, adopting digital twinning approach, instead of developing models, *modeling engines* with several functionalities (see Fig. 7) are required to be developed. The main steps of developing DT for MGs are summarized in Fig. 8.

## III. DIGITAL TWIN APPLICATIONS IN MICROGRIDS

During the last decades, with the increasing global concerns over the depletion of natural resources and environmental pollution along with technological advances in deploying renewable-based energy sources, MGs have become an integral part of the modern power systems. According to the US Department of Energy, a MG is defined as *a group of interconnected loads and distributed energy resources (DERs) within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A MG can connect and disconnect from the grid to enable it to operate in both grid-connected or island mode* [53]. MGs' mission is to enhance the performance of energy systems in terms of system efficiency, life cycle cost, quality of services, asset management, and sustainability. Accordingly, optimality, autonomy, reliability, resiliency, safety, and being environmentally friendly are among the main features of the MGs operation.

During the last two decades, a large body of research has been conducted to enhance the MGs operation addressing one or some of these aspects [54], [55]. However, investigating the role of the DT as a new tool to assist in the design, development, and control of MGs and its effectiveness for enhancing the performance of MGs is a quite new research area. In this section, potential applications of the DT in MGs will be explored and the recently published studies that applied the DT concept to power system applications and specifically MGs are reviewed. A general overview of the DT important services in MGs is provided in Fig. 9.

### A. MICROGRIDS DESIGN AND DEVELOPMENT

At the design and planning stages of MGs, the virtual models can be first developed and even delivered in advance [6]. The MGDT provides the designers with an advanced tool to assess the MG performance from different points of view and under various operating conditions. Therefore, the required changes
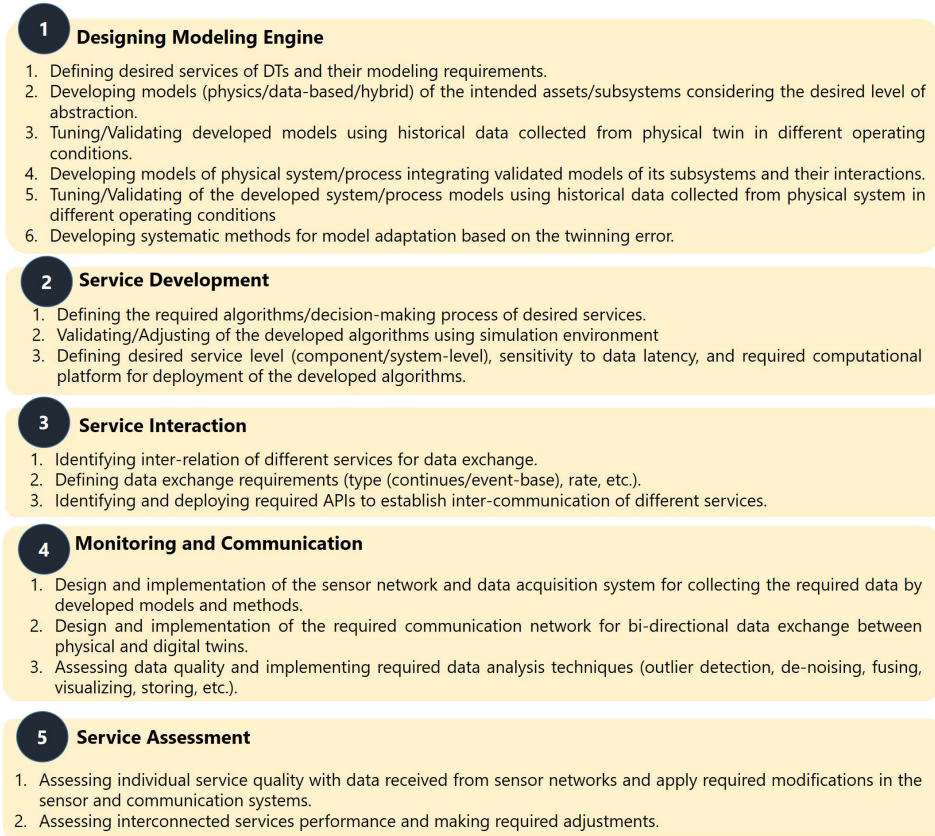
**1  Designing Modeling Engine**

1. Defining desired services of DTs and their modeling requirements.
2. Developing models (physics/data-based/hybrid) of the intended assets/subsystems considering the desired level of abstraction.
3. Tuning/Validating developed models using historical data collected from physical twin in different operating conditions.
4. Developing models of physical system/process integrating validated models of its subsystems and their interactions.
5. Tuning/Validating of the developed system/process models using historical data collected from physical system in different operating conditions
6. Developing systematic methods for model adaptation based on the twinning error.

**2  Service Development**

1. Defining the required algorithms/decision-making process of desired services.
2. Validating/Adjusting of the developed algorithms using simulation environment
3. Defining desired service level (component/system-level), sensitivity to data latency, and required computational platform for deployment of the developed algorithms.

**3  Service Interaction**

1. Identifying inter-relation of different services for data exchange.
2. Defining data exchange requirements (type (continues/event-base), rate, etc.).
3. Identifying and deploying required APIs to establish inter-communication of different services.

**4  Monitoring and Communication**

1. Design and implementation of the sensor network and data acquisition system for collecting the required data by developed models and methods.
2. Design and implementation of the required communication network for bi-directional data exchange between physical and digital twins.
3. Assessing data quality and implementing required data analysis techniques (outlier detection, de-noising, fusing, visualizing, storing, etc.).

**5  Service Assessment**

1. Assessing individual service quality with data received from sensor networks and apply required modifications in the sensor and communication systems.
2. Assessing interconnected services performance and making required adjustments.

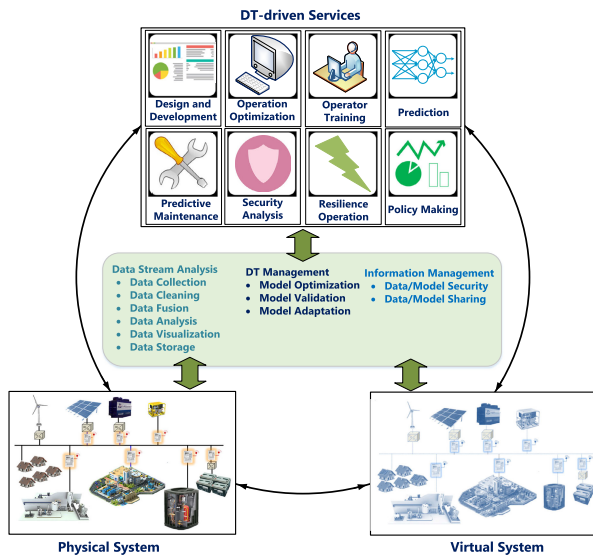**FIGURE 8.** Digital-twinning work flow.



**FIGURE 9.** Digital-twinning services in MGs.

can be made at the early stages of development [29]. Besides, potential implementation risks can be identified and mitigated, thereby increasing the confidence in the final design. NASA and US Air Force apply DT technology in vehicle development in the product design phase [25]. Airbus Iron bird is an example of developing a *hardware twin* integrating the electrics, hydraulics, and flight controls of the aircraft in an easy-to-access framework for design validation [56]. The advantages of using MGDTs for the design purpose stems from their capability to provide a high fidelity simulation platform for designing, testing, and assessing MGs. Different scenarios ranging from normal operating conditions to extreme events can be simulated to analyze the efficiency, reliability, and resiliency of different designs. Besides, the appropriate size and capacity of system equipment (generators, transformers, lines, switches, converters, energy storage systems (ESSs), renewable energy sources (RESs), and so on) and the required reserve capacity can be efficiently determined. This is extremely important in MGs applications in isolated or hostile environments such as space MGs or terrestrial MGs in remote areas and polar latitudes.

Regarding the planning (siting and sizing) of RESs, the MGDT will be exposed to a similar environment that is experienced by the real system simulated using the historical data. Besides, reliable models and advanced ML tools are deployed to predict the output power of RESs. Digital models will account for the uncertainty resulting from variations in wind speed, solar radiation, ambient temperature, and other environmental characteristics. Thus, more accurate investment plans can be made reducing the investors' and operators' uncertainty to invest in green technologies. As a

result, more renewable-based power will be introduced in the system reducing electricity generation environmental impacts and $CO_2$ emission. The developed validated virtual model could be handed over in advance to consider possible design changes [6].

The MGDT provides an accurate representation of the MGs' load and its evolution over time. This is achieved through deploying different very short-term, short-term, medium-term, and long-term forecasting models of MGs load [57] enriched with real-time data. Employing the long-term load and RESs forecasting models with ESSs models provides the opportunity of revising the system design in a low-cost environment. Besides, the degradation models of RESs and ESSs are used to estimate their useful life under realistic operating conditions. Such a comprehensive reference model of the system will help design cost-effective sustainable MGs with the lowest implementation risk.

In [58], a DT as a building information model is developed to evaluate the net-zero energy building (NZEB) concept for existing buildings. After creating the model, different analyses are performed to calculate the cost-saving and payback of NZEBs considering different technologies.

As a digital representation of the physical system, the MGDTs can be employed in a variety of what-if scenarios to simulate the state of the behavior of a MG in different normal, emergency, or faulty operating conditions and record the observed behavior. The result will be a valuable dataset, which is difficult to obtain from the physical system without compromising its safety. This dataset can be used as a rich training dataset for training different ML models with different purposes such as security analysis, fault detection, and fault diagnosis or training human/autonomous operators. The digital representation of the physical system, which is used for simulating the system behavior in non-real-time applications is called *Digital sibling* in [39]. In [59], a two-phase fault diagnosis model is proposed. First, the model is fully trained based on the train dataset generated by the virtual model while at the second phase, the trained model is migrated from virtual to physical space by using *deep transfer learning*.

## B. FORECASTING AND FLEXIBILITY IDENTIFICATION
Forecasting is one of the most significant tasks of MGs. Specifically, considering the uncertain nature of the produced power of RESs, developing efficient forecasters to determine the MG available power is crucial. By improving the prediction accuracy, the reliability of the energy supply will be increased and the need for over-sizing system equipment and deploying large-size reservoirs will be reduced. Therefore, maximum resource utilization can be ensured. Further, accurate predictions of the RESs available power will facilitate their participation in ancillary services (frequency/voltage regulation, reactive power support, black start services, etc.) to ensure MGs reliable and secure operation [60], [61].

Different physics-based, data-driven, and hybrid techniques for estimating the output power of RESs across various

timescales (very short-term [62], [63], short-term [64], [65], medium-term [66], and long-term [67], [68]) can be found in the literature [69]. In recent years, deep learning-based methods are becoming increasingly attractive for predicting meteorological parameters (wind, temperature, and radiation) and RESs power estimation. Specifically, Recurrent Neural Network models consisting of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), as well as Convolutional Neural Networks (CNN) are among the widely used data-driven techniques. An up-to-date overview and classification of deep learning-based wind and solar power forecasting methods can be found in [70].

In data-driven forecasting methods or physics-based and hybrid models that require parameter tuning, adapting the forecasting model with up-to-date data on an ongoing basis results in an accurate dynamic forecasting method. Thereby, an efficient data management system is needed to collect, process, and systematically share the required data for autonomous adaptation of the forecasting models.

Specifically, in case all the required data are not directly collected from the field and need to be obtained from other sources (total sky imagery, satellite imagery, meteorological forecast, nearby sites, etc.), efficient interaction among various data sources is essential (see Fig. 10). In this sense, DT is recognized as an efficient tool to enhance the autonomy and efficiency of forecasting techniques for MGs. In [60], a very short-term temperature forecaster is proposed for estimating the output power of PV systems. To do so, the temperature dataset of nearby locations around the target site is also used to improve the prediction accuracy. By adopting the DT technology in this case, the interoperability of the nearby solar farms and MGs will be enhanced through sharing the up-to-date data efficiently. Besides, this example shows how
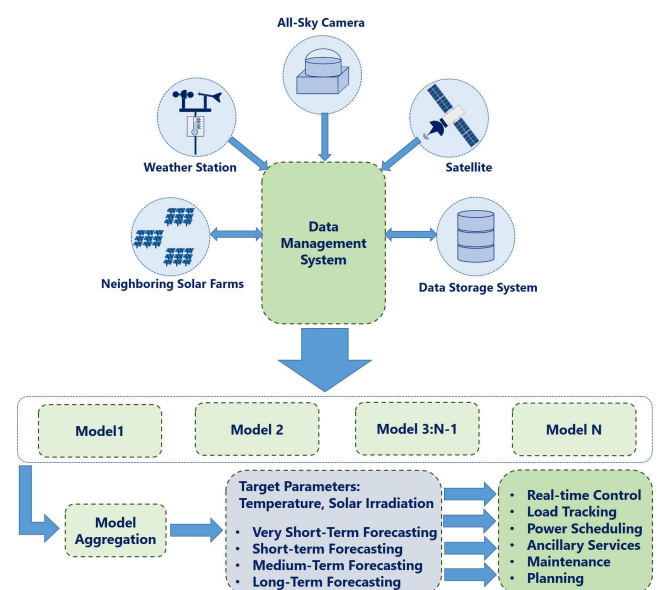


**FIGURE 10.** An example of using multiple-sources data for PV! power forecasting in MGs.

the DT of other systems in the proximity of a new-built site can help to build its DT.

It is worth noticing that DT has a long history in meteorological institutes [39].

Similar to other systems that interact with human beings, human behavior is one of the main sources of uncertainty in MGs. With the increasing integration of residential WTs and PV panels and decreasing the ESSs prices, consumers take more active participation in MGs operation. Hence, predicting their electricity usage patterns is becoming more complex and challenging. Furthermore, with the introduction of smart home appliances such as washing machines, dishwashers, clothes dryers, electric water heaters, and air conditioners, consumers can manage their power consumption pattern more proactively and participate in demand response (DR) programs.

In addition, increasing the integration of electric vehicles (EVs) into MGs calls for advanced analytics tools to explore their charging patterns. Also, with the growing vehicle-to-grid (V2G) technologies, EVs offer many services as mobile ESS to stabilize MGs [43].

Although the emergence of these new applications in the consumers-side introduces new challenges and complicates the operation management of MGs, it brings many advantages to support their flexible and efficient operation. However, effective utilization of these flexibility resources requires up-to-date knowledge of the consumers' facilities and their power usage/generation patterns [47], [71]. Hence, a huge amount of data is continuously collected from the metering devices across the MG and processed for load profiling and electricity usage pattern recognition. Besides, several studies use the driving statistics and the collected data from charging stations to model the charging patterns of EVs at homes or public charging stations [72]. Accurate spatial and temporal distribution prediction of EVs is very important for operation management and planning of MGs and charging stations.

In this regard, the MGDT is expected to support the identification of the flexibility sources on the consumer-side and power consumption patterns of MGs consumers in several ways. First of all, the advanced data management system offered by the MGDT enables the efficient organization and process of the historical data and the real-time data stream while preserving data integrity and privacy. Besides, the MGDT provides a high-fidelity simulation platform for modeling the prosumers'/consumers' behavior. As a matter of fact, the MGDT offers a dynamic and interactive platform for modeling the consumers' response to different stimuli such as electricity price and DR incentives as well as predicting their power consumption under different conditions (weather conditions, time of day/week/year, etc.). In this sense, the DT is perceived as a game-changing tool in human interactive systems like MGs. Furthermore, the DT will facilitate the systematic integration of different data sources and forecasting methodologies. Using fusion techniques at the different sensor, feature extraction, and decision levels will enhance the accuracy of the forecaster outcome [73].

Electricity market price is another source of uncertainty in MGs operations. Accurate forecasting of electricity prices requires precise modeling of market dynamics and the interaction of different players which can be achieved in the light of digital twinning.

## C. CONTROL AND OPERATION MANAGEMENT

After validating the digital models accuracy, the MGDT can be used as a powerful tool in a DSS for MG control and operation management running in parallel with the physical system [5]. The MGDT will assist the operators in MGs transients and steady-state assessment, detecting critical operating conditions, analyzing system performance, and making fast decisions in response to changes in the system.

Besides, accessing the information of operating conditions of individual components, their SoH, remaining useful life (RUL), and degradation trend provided by the MGDT, the supervisory controller can make the best operating schedule. For instance, the EMS can reduce the stress on a storage device by limiting its utilization and adjusting its operational constraints (charging/discharging cycles, power limits, depth of discharge, and so on) accounting for the RUL of the battery received from its DT. These predictive actions can postpone the maintenance and replacement time of equipment to a time that results in the minimum cost and performance degradation of the system. Besides, in case a second life is considered for the component, for example using the battery of a satellite or EV in a stationary application, the best transition time can be scheduled- supporting the growing interest in *circular economy*.

Using the MGDT, the performance of different control strategies and operation management methods can be thoroughly studied. Exploiting the full potential of the mature simulation environment, the effectiveness of the proposed control techniques can be validated under various operating conditions. Even, the MGDT will help to evaluate the effects of system operation management techniques on the system lifetime and degradation trends. Hence, the required corrections can be made in advance. This is one of the most attractive applications of the DT in healthcare systems, helping people to promote their lifestyles and take necessary precautions to prevent disease to occur and prolong their healthy life.

The DT will also improve the performance of remote control systems. Remote real-time supervisory and control centers can benefit from a highly reliable and dynamic model of the physical system to adjust the control strategy. A good example is a space MG (such as a spacecraft or a lunar habitat [74]) where maintenance and replacement of system components cannot be easily performed [75]. Hence, a reliable control system, which can efficiently manage the resources and distribute the power based on each subsystem operating conditions, SoH and RUL is of vital importance.

In the light of DT-driven power generation and consumption forecasting techniques, the uncertainty in the available power of RESs and power consumption will be reduced. As a

result, more efficient EMSs can be designed to improve MGs' performance in terms of operation cost and environmental impacts with maximum RES utilization. The DT will allow modeling consumers behavioral patterns and their interaction with the MG. Thereby, allowing the control centers to implement advanced operation management and demand-side strategies.

To ensure real-time operation of the controller in response to dynamic changes, field programmable gate array (FPGA) that provides low latency and massive parallelism can be used for implementing the controllers [76]. In [20], a DT-driven framework for online analysis of a large-scale power grid (40k+ buses) is developed. The results show that using DT, the response time from data acquisition to complete analysis reduces from the current approximate time of 10 min to 60 sec. The proposed DT features *in-memory and parallel computing*, complex event processing, and ML-based security assessment.

### D. OPERATOR TRAINING AND MG AUTONOMY
The MGDT provides an advanced platform to train the MGs human and machine operators in a low-cost low-risk environment. Training the human operator in a dynamic environment can result in broadening their experiences in controlling the MGs operation especially under adverse and emergency operating conditions. Besides, the MGDT can be used to train the human operators in MG maintenance services.

Thus, an efficient human-machine-interface (HMI) to facilitate the simple interaction of the MGDT and human operators should be developed. In this regard, virtual reality (VR) and AR are attracting a grate deal of attention. A more detailed discussion on VR, AR, and natural language processing to implement the HMI can be found in [39] and the references therein.

In autonomous systems, the automatic operator is trained during the life cycle of the system by updating its experience in a systematic learning process [20], [77]. Automatic learning will enhance the operators' decision-making abilities while the detrimental effects of wrong or inaccurate decisions will be reduced.

System autonomy is defined as *the capability of the system in responding to unexpected events without the need for a central reconfiguration and re-planning* [23]. To improve the autonomous characteristics of MGs, establishing a highly reliable representation of the system as a reference model is of vital importance. The MGDT will help the autonomous control system improve its self-awareness by (a) representing a holistic up-to-date dynamic view of the physical system operating conditions and assets situation, and (b) providing high-fidelity simulation platforms to simulate its evolution and projecting its future condition. Relying on the built-in feedback process of the DT, any discrepancy between the physical system and its reference model will be detected in a timely fashion, which could prevent the system from severe damages. The built-in self-adaptive characteristic of the MGDT will result in the adaptation of the digital model

and consequently the control strategies to the dynamic environment in a systematic manner.

MGs *self-healing* which is also an important characteristic of autonomous systems could be vastly improved with the advent of digital twinning. In case of performance degradation due to the fault occurrence or an unforeseen change (load changes, generation loss, line outage, etc.) in the system, a DT-based DSS can recommend or implement (in case of fully autonomous systems) the required actions to mitigate potential damages. A switching control strategy can be implemented to change the operating strategy from normal to abnormal and urgent operation and activate self-healing mechanisms after detecting an anomaly in system operation. For instance, by continuously monitoring the state of several indicating parameters identified through what-if scenarios as part of the training process. A hierarchical operation management scheme for multi-microgrid systems during emergency conditions is proposed in [78].

Equipment-embedded DT-based DSSs will support the system self-healing through optimizing the operating strategy at the device level without operator intervention. Edge and fog computing platforms present a promising solution to enhance self-healing due to the lower latency.

Last but not least, in case of communication failure or data loss, a recent record of the system state of behavior provided by the MGDT will help the operators to tolerate the abnormal situation and restore the system to a normal (sub-optimal) condition.

### E. STATE OF HEALTH MONITORING AND PREDICTIVE MAINTENANCE
Aging is an inevitable phenomenon in every physical system, which can result in degrading the system performance and increase the operating cost in the long term. Hence, capturing system degradation and aging management are among the main requirements of MGs. Besides, to make sure that all system equipment meets the operating requirements, an effective maintenance procedure is required. Therefore, MGs and in general power systems require accurate inspection and timely repairing and replacement of components to preserve the service quality and continuity. In this sense, a large share of the MGs cost is related to their periodic maintenance that significantly increases for equipment and components, which cannot be easily accessed, for instance offshore WTs or MGs in geographical islands and rural areas.

To improve the MGs reliability and prolong their equipment lifetime, advanced monitoring systems are required to analyze components conditions during operation time. Further, knowing the exact location of the system's assets (both personnel and components) will considerably enhance operation management of the system especially under adverse operating conditions.

The digital twinning concept can be applied to the condition and SoH monitoring of systems and equipment. From an asset management point of view, DT is a powerful tool for locating the assets and early detection of anomalies in

asset performance and call for predictive actions. Hence, periodic and preventive maintenance will be replaced with predictive maintenance resulting in more efficient and less costly maintenance procedures.

The MGDT will help to integrate the available information obtained from analyzing historical and real-time data with analytical models. Hence, informative indices representing the current state of the assets and their future projection can be evaluated and visualized through the HMI. Therefore, it provides a platform to closely monitor SoH of the assets and estimate their RUL. This information will be shared with control centers and maintenance management systems to adjust the operating strategy and prepare the optimum maintenance schedule, respectively.

In [13], a physics-based DT with 3-D models are developed for an automotive braking system for heat monitoring and predictive maintenance purposes. In [79], a data-driven DT is used to estimate the speed loss of the ship's hull and propeller due to the marine fouling. The deep learning method is used to develop the DT using the data gathered from the onboard sensors during different operational and environmental conditions when the fouling is not present. The RUL of the power converter of fixed and floating offshore WTs is estimated using DT in [80]. Thermal loading of power converters due to the environmental conditions, the mechanical structure of WTs, and the electrical system are modeled to govern the IGBT junction temperature and its fluctuations. In [81], the DT concept is adopted for degradation assessment and SoH monitoring of a Lithium-ion battery pack in a spacecraft. The State of charge (SOC) of the battery cells is estimated by using Kalman Filter - Least Squares Support Vector Machine algorithm. While the SoH of the battery pack is evaluated via the Auto Regression model-Particle Filter algorithm using real-time and historical data. In [82], DT-based supervision of automotive battery systems throughout different life cycle stages of production, utilization, second life usage, and recycling is presented. In [83], the DT concept is used to develop an electric-thermal model of a battery system that, in combination with an aging model, is used to monitor the battery degradation and calculate the residual value for the potential second-life applications. The DT-based SoH monitoring and predicting the RUL of the traction motor of EVs is studied in [84]. Both *In-house* and *remote monitoring* approaches are considered. The model can assist the user and service companies to find the best time to refill the bearing lubricant.

### F. FAULT DIAGNOSIS
Fault diagnosis is an important task in MGs. Detecting the fault occurrence, identifying the fault type, and prescribing the required actions are among the most significant steps after a fault event. An efficient fault diagnosis system improves the MG reliability by reducing the system downtime and associated consequences such as loss of load, outage cost, and system stress among others. Since physical access to the system is difficult in many cases due to the complex installation, hazardous situation, and time-consuming and costly procedure, reliable and cost-effective fault diagnosis methods are highly required [85]. In this sense, the MGDT as a high-fidelity model of the real system running in parallel can be used to detect any malfunctioning of different parts of the system as well as controllers and sensors. Besides, faulty operation of the system can be detected by continuously comparing the system performance with the reference behavior.

Preparation of the DT to support fault injection is studied in [86]. In [85], the DT concept is applied to develop a fault diagnosis system for a PV energy conversion unit consisting of a PV panel and the power converter. Ten different faults in the PV panel, power converter, and electrical sensors are considered. The authors also used the DT to create the fault signature library. In [2], a DT reference model for fault diagnosis of a rotating machinery is proposed. Besides, to improve the adaptability of the model, a model updating strategy is provided. In [76], to detect abnormalities in the physical subsystems of a power converter, a controller-embedded DT-based diagnostics monitoring system is proposed. The digital models are embedded with the controller and benefit from the computational capability of FPGAs. In [87], a DT-based approach is proposed to localize the imbalance state of the rotor system and predict the rotor temperature in an electric drive train.

### G. MICROGRID SECURITY, RESILIENCY, AND SITUATIONAL AWARENESS
MGs have two interdependent layers namely the physical layer and the cyber layer. Consequently, to ensure the secure operation of the system, MGs should be protected against potential threats in both layers [88].

System security is defined as *reducing the risk of the system critical infrastructures damages from natural disasters or adversarial hazards (intrusions, malicious attacks, etc.)* [89]. Dynamic security analysis is essential for the safe operation of MGs. Digital twinning will provide a platform to identify and simulate possible attack scenarios in MGs. Thus, timely detection of potential situations that might lead to insecure operation can be achieved by either relying on data-driven methods or projecting the system behavior using the DT-based simulation platform. Accordingly, the required remedial actions will be prescribed. Besides, the MGDT will support constant improving of the MGs security considering new threats in an automatic manner.

In [88], a DT named ANGEL is developed for the CPS security of MGs. To mitigate component failures and cyber attacks, the potential of ANGEL for protecting both the physical and the cyber layers of MGs are discussed. The IEEE 39-bus system is used as a benchmark. In the Agile security (AgiSec) methodology introduced in [90], a comprehensive attack graph representing all the potential cyber attack paths is constructed and automatically updated. Based on the attack graph, remediation requirements to avoid the most probable attacks are identified. Integrating this method with the DT concept will address AgiSec's concerns over the lack of comprehensive models of system processes. In [91], the

real-time security risk assessment is studied in the State Grid, China in a DT-based framework. The physical and virtual systems are connected through the SCADA RTU system.

One of the key security and resilience aspects of MGs is SA. The *perception of a system and associated subsystems in relation to its environment and projection of its states in the near future* is defined as SA [21], [46], [92]. Considering the growing complexity and inter-connectivity of energy systems, SA is of vital importance for system operators and DSSs. With enough SA, system operators will be able to take the required actions on time to prevent fault propagation and minimize its impacts on operation of their responsibility area as well as adjacent interconnected networks [93], [94]. Effects of SA on the reliability of power systems are discussed in [93]. The MGDT supports SA of MGs in several ways. First of all, it facilitates the handling of enormous data in a systematic manner applying advanced data analytics techniques for data pre-processing, outlier detection, storage, etc. as discussed in previous sections. Besides, using high-fidelity models and DT-driven simulation platforms support providing a more accurate picture of the system and a higher level of comprehension of the current and future state of the system. Such visibility can be complemented by the DT HMI solutions (3D visualization, AR, VR, etc.) for better interaction and training of system operators. Enhancing cyber SA using digital twinning concept is studied in [95].

SA plays an important role in improving the MGs' resilience. System resilience is defined as *the ability of the system to anticipate high-impact low-priority (HILP)* events, rapidly recovering from these events, and learning lessons for adapting system operation and structure to be better prepared for future events [96]. In [96], fundamental concepts of power systems resilience and key resilience features of power systems at different states of event progress from pre-disturbance to post-restoration states are thoroughly discussed. These fundamental properties are *Anticipation*, *Absorption*, *Recovery and Restoration*, and *Adapting* after damaging events. To be able to anticipate the HILP events and rapidly recover from them, MGs should boost their SA and operational flexibility to take timely preventive, corrective, and restorative actions [96], [97]. The MGDT enables operational flexibility of MGs by providing them with:

- Improved SA and accurate up-to-date digital representation of the state of the system presented through advanced visualization tools,
- An advanced asset (personnel, stationary and mobile distributed resources, voltage control support equipment (reactors and capacitors) [61], etc.) management system with accurate information of assets location and status,
- A high-fidelity simulation platform to project system behavior and assess the effects of preventive, corrective, and restorative actions,
- Advanced highly trained DSSs to prioritize re-energizing MGs lines and components and coordinate restoration actions based on the adaptive training techniques,

- Automatic update of event models using MGDT modeling engines and adaptation of preventive, corrective, and restorative actions by properly training of the DSS for future events using advanced ML techniques.

Further, DT-DT communication enables advanced operation coordination of neighboring MGs as well as interdependent infrastructures such as electrical systems, gas networks, water supply systems, transportation and communication systems, etc. Considering the inter-dependency of different networks is a critical and challenging task of restoration from outages caused by natural disasters [97].

Regarding cyber resiliency, restoring the recently updated models and relying on soft sensors in case of loss of sensors can help operators to maintain/recover system operation. Fig. 11 adapted from [96] represents a visual tool to show "qualitatively" how the MGDT can help to enhance the resilience operation of MGs by reducing the level of degradation, speed of the resilience degradation (slope of lines), and duration of different phases. It is worth noting that Fig. 11 is a qualitative figure for visualizing how the improvements will affect the resilience trapezoid, which needs to be supported by a quantitative analysis that is the scope of future research of the authors. The roles of MGDT in boosting MGs' resiliency in different phases of the catastrophic event progress are summarized in Table 2. Using the MGDT, different kinds of threats including natural (hurricanes, storms, earthquakes, etc.), technical (grid outage, generator, power or communication line failure, ESS damage, etc.), and human-induced hazards (cyber-attack, malicious attacks, etc.) can be analyzed. The results will help operators to have a more accurate classification of abnormal situations and investigate the system behavior under different adverse operating conditions. Efficient mitigation strategies in pre-, during, and post-fault/disaster phases can be devised and organized in different forms such as rule-based methodologies, look-up tables, and technical procedures. Therefore, more efficient preventive actions, as well as absorption and recovery from different system faults and disruptive events, can be taken. Specifically, in situations where a catastrophic phenomenon is propagating quickly, the reaction of system operators could be significantly improved by receiving assistance from the DT-based DSS. Besides, these operating strategies can be used to train the DSS for future events. The proposed DT-enabled conceptual model to enhance the MGs resilient operation is presented in Fig. 12.

In [98], a digital replica of a power system is used to detect the event of fault-induced dynamic voltage recovery and predict the post fault dynamic behavior. It is proposed that with the timely prediction of the fault dynamic in a faster than the real-time digital replica, the appropriate control action such as under-voltage load shedding could be determined. For validation purposes, the real system is simulated in the real-time digital simulator (RTDS) with RSCAD software, while Digsilent PowerFactory software is used for simulating the digital replica. The concept of DT is used for DERs and distributed controller design in [99]. DT is deployed

**TABLE 2.** MGDT role in boosting MGs resiliency.

| Phase | Type of action [96], [97] | key resilience feature [96] | MGDT role | Impact [96] |
|---|---|---|---|---|
| Pre-disturbance | **Preventive actions**<br>• DERs allocation<br>• Load re-dispatch (considering load priorities)<br>• System reconfiguration (islanding, clustering, etc.)<br>• Pre-positioning of the resources (crews, mobile generators, mobile ESSs, etc.)<br>• Setting up reserve resources | Estimation of event location and its severity with sufficient accuracy | • Providing an up-to-date picture of the current state of the system based on the real-time data connection and accurate modeling and estimation techniques<br>• Providing an advanced asset management system using the historical and real-time data<br>• Improving the accuracy of predicting load profile and available power of RESs using adaptive data-driven and model-based techniques and model integration/fusion methods<br>• Providing a high-fidelity virtual platform to project system behavior<br>• Facilitating the interaction with other interdependent systems and adjacent networks | Improving operational flexibility |
| Disturbance progress | **Emergency actions**<br>• DERs re-dispatch<br>• Load shedding<br>• MGs reconfiguration, islanding schemes, etc. | Advanced monitoring and information systems to inform about the evolving conditions (sufficient SA) | • Providing an up-to-date picture of the evolving state of the system based on the real-time data connection (as well as soft sensors) and advanced visualization tools<br>• Improving absorption property of MG by timely triggering the required functions through representing the evolving condition of the system in a faster than reality environment. | Reducing the speed/level of performance degradation |
| Post-disturbance | **Emergency coordination**<br>• Damage assessment<br>• Identifying critical components for restoration | Disaster assessment and priority setting for quick commencement of system recovery | • Providing advanced highly-trained DSSs to help with prioritizing MGs lines and components for re-energizing and optimal crew allocation based on offline training<br>• Improved SA and up-to-date picture of the current state of the system to assess damage impacts | Fast commencement of system restoration |
| Restorative state | **Restorative actions**<br>• Re-energizing lines<br>• Load restoration<br>• Re-synchronization | Coordination of restorative actions | • Providing advanced highly-trained DSSs to help with coordination of restoration actions based on the offline training and evaluating the actions consequences using high-fidelity virtual platforms | Fast system recovery |
| Post-restoration | **Adaptive actions**<br>• Assessment of disaster impacts on system resilience and performance<br>• Adapting actions for better dealing with future events | Adaptation of actions during different states | • Automatic updating of event progress models<br>• Automatic adaptation of the preventive, corrective, and restorative actions to properly re-train the DSS for future events using real data gathered during different stages of event progress | Improving system operational and infrastructure resilience |

in [100] for assessing the MGs controllers performance in terms of reliability, resiliency, and efficiency. Digital twinning approach is also followed in [101] to evaluate the MGs' resilient operation and identify potential risks before constructing the MGs. Oak Ridge National Lab is studying the cyber attack issues and physical damage imposed by weather conditions. DT is used to cut the power in parts of the grid that might result in cascading failures [102]. Edge-deployed DTs are developed by ABB to provide a virtual simulation environment for real-time performance assessment to boost resilience operation of the MGs [103].

### H. EXPANSION PLANNING AND POLICY-MAKING
Power systems are continuously undergoing changes in the power generation capacity and technologies, which are mainly due to the increase of the power demand and new regulatory rules. In this regard, the expansion planning of energy systems has always been among the key issues of both academia and industry. Expansion planning is a strategic decision that affects the economic benefits of power companies and their level of competence. Therefore, the expansion decision should be made with a sufficiently accurate prediction of the system behavior in the long-term regarding demand growth, technology trend, and possible changes in regulatory rules among others. In this sense, the MGDT can provide a highly reliable and less costly platform to model the MG ecosystem and perform long-term simulation analyses to find the best time and strategy for the expansion planning.

Furthermore, the main concern over making new policies or changing the current strategies has always been the response of different subsystems and players being affected by the associated consequences. Besides, the compatibility
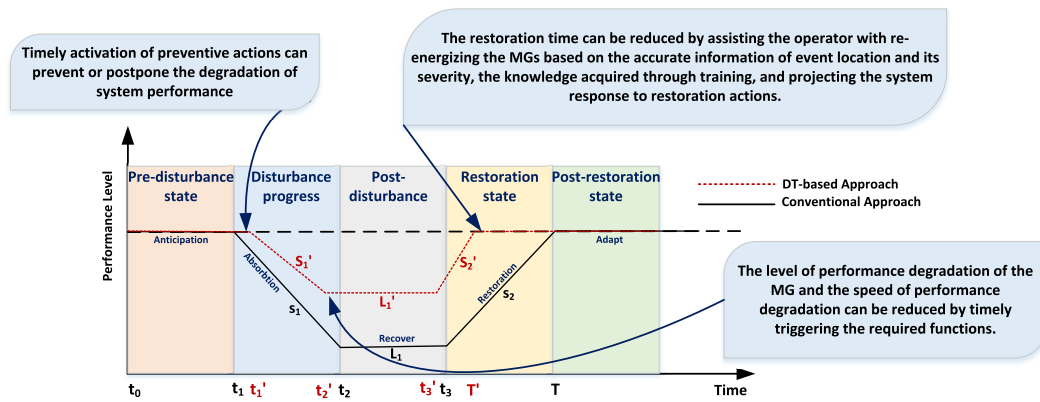
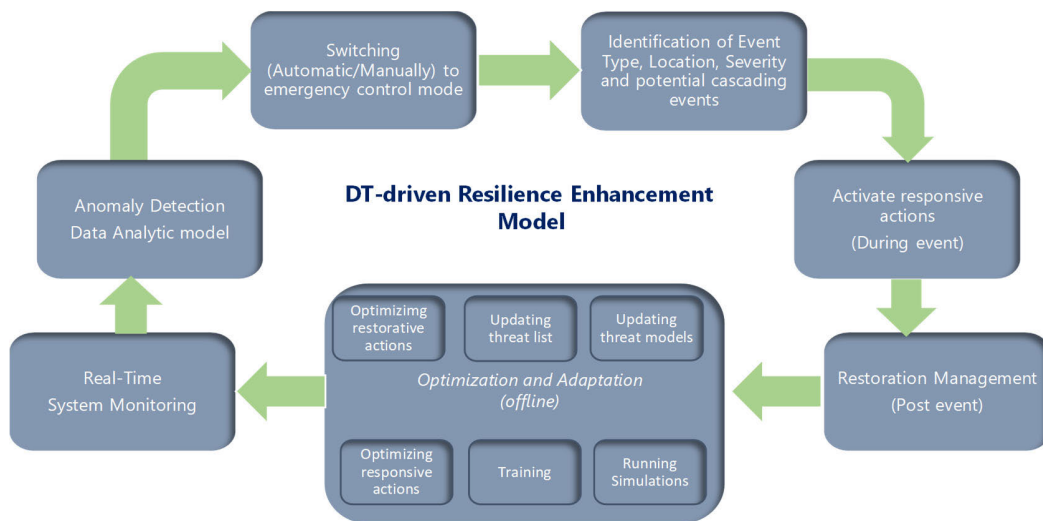**FIGURE 11. Microgrids resilience adopting MGDT concept.**



**FIGURE 12. Proposed DT-driven MG resilience enhancement conceptual model.**

of the long-term outcomes of the new policies with the policymakers' intentions is required to be analyzed before proceeding to implement them. In light of MGDTs, an efficient testbed is provided to predict the system's response to different future scenarios in different time horizons. Relying on a dynamic and highly reliable model, short-term and long-term impacts of different incentives, DR strategies, and electricity price schemes can be studied. Besides, opportunities and barriers for adoption of new technologies, such as the substitution of conventional diesel generators by hybrid ESSs and RESs or impacts of high integration of EVs and the hosting capacity of electricity distribution grids can be thoroughly analyzed. As a conclusion, Table 3 presents an overview of recent studies on MGs and DERs with digital twining approach.

## IV. LOOKING TO THE FUTURE

Advances in information, communication, and sensor technologies make the DT a new paradigm for the digitalization

of many industries including power systems. However, taking full advantage of digital twinning in MGs requires the synergy among different fields of expertise to create a digital ecosystem interconnecting data, software, and hardware [104].

- Considering the significant role of data in establishing the DTs, well-developed infrastructures for collecting high-quality and high-resolution data and analyzing them are required. Although the existing IoT and monitoring platforms in MGs provide a good foundation, to enhance the efficiency of data analysis, sensor nodes require to be enhanced to perform some local analyses, which demands more advanced monitoring infrastructures.

- To reduce the data transmission latency and high bandwidth requirements and to enhance data privacy, edge intelligence (implementing the AI at the network edge) is recognized as a promising solution to perform data analysis in the proximity of the data source [49]. In MGs, due to the growing integration of DERs and

**TABLE 3.** Classification of recent studies on MGs and DERs with digital twining approach.

| Area | Reference | Application |
|---|---|---|
| Design, monitoring, and operation management | [108], [109] | VPP operation management |
| | [110] | District EMS |
| | [111] | Monitoring and control of current source inverters |
| | [48] | Wind farm monitoring and analysis |
| | [112] | Power transformer monitoring |
| | [113] | Renewable energy generator twinning |
| | [114] | CPSs twinning |
| | [115] | Microgrid design and EMS |
| | [116] | Smart home management |
| SoH monitoring and predictive maintenance | [117] | Power transformer SoH monitoring |
| | [118] | Anomaly detection of battery |
| | [119] | Prognostics and health management of a WT gearbox |
| | [80] | Estimating RUL of the power converter of fixed and floating offshore WTs |
| | [81] | SoH monitoring of a Lithium-ion battery pack in a spacecraft |
| | [83] | Monitoring battery degradation |
| | [120] | Lithium-ion and lead-acid battery management systems |
| Fault diagnosis | [85] | Fault diagnosis system for a PV energy conversion unit |
| | [76] | Anomaly detection of a power converter |
| Security, resiliency, and SA | [88] | CPS security of MGs |
| | [91] | Real-time security risk assessment |
| | [100] | Assessing the MGs controllers performance in terms of reliability, resiliency, and efficiency |
| | [121] | Cyber security-False data injection and the denial of service cyber-attacks |
| | [101] | Evaluating MGs' resilience operation |

electricity users, edge computing has been attracting a great deal of attention over the last few years. Fault detection, monitoring SoH of the electrical equipment, and power quality services are among the tasks that can be totally/partially assigned to the edge [105]. Accordingly, integrating the strength of edge technology and DT in MGs is a promising research area for future studies.

- Realizing the MGDT requires high-performance hardware and software infrastructures for executing the AI algorithms and solving mathematical models in the required time. Using FPGAs and relying on parallel computing and on-demand cloud services and graphics processing unit (GPUs) [106] are among the current solutions for this issue.

- Standardization of the DTs modeling, data storage [35], [104], communication among different entities (DT-DT, DT-service center, DT-data source, and so on), as well as security of MGs' data and digital assets deserve the attention of industrial and research societies.

- Regarding cybersecurity, recent advances in the *blockchain* technology in MGs provide a promising solution for the advanced tracing of digital assets and minimizing the risk of tampering with data records and information [107]. Transparency and security provided by blockchain technology will increase the trust for data and information sharing among different MGs

applications and authorized entities. Thus, blockchain-based data management for DTs need to be further explored in the context of MGs.

- Another important feature of MGDTs, which demands their modular design is related to DT-DT interconnection and communication requirement. In this sense, DTs that are developed for the neighboring subsystems (such as different MGs in a multi-microgrid system, neighboring wind, and solar farms, etc.) or interdependent infrastructures (such as electricity, transportation, natural gas, communication, water, and heating supply systems, etc.) could be efficiently linked and provide the systems with an unprecedented level of interoperability and synergy. Accordingly, a cooperation platform will be created, which offers enormous potentials to boost power systems efficiency, performance, and resilience operation.

## V. CONCLUSION

This paper aimed to introduce the MGDT concept and the applications of digital twinning in MGs. The concept of DT and its key characteristics were reviewed and the key enabling technologies for digital twinning were explored. The need for the MGDT stems from the growing complexity of electrical systems and equipment, which requires their close inspection and timely maintenance. Specifically, those assets, which are not easily accessible, require real-time remote monitoring and predictive maintenance. Furthermore, with the extensive integration of data acquisition technologies into the MGs and the availability of high-frequency high-quality data, systematic ways to manage the data are highly required. Accordingly, the operation strategies can be dynamically adapted to improve the system performance. The increasing penetration of RESs into the MGs and the emergence of prosumers are also demanding accurate dynamic forecasting techniques as well as automatic learning of behavioral patterns of prosumers. Finally, the growing dependency of other critical infrastructures such as healthcare, transportation, telecommunication, water systems, etc. on electric systems demands a highly reliable supply of energy with minimum service interruption and downtime.

The MGDT in its fully developed form will provide a well-structured and systematic way for information and data management of systems' assets, which facilitates their close tracking during their lifetime. Besides, the information stored in the standard format can be shared among authorized entities and stakeholders to be used for different analyses.

The MGDT will support the accurate prediction of RESs power supply and prosumers' behavior taking advantage of well-structured historical and real-time data and high-fidelity models. Benefiting from the enhanced SAs and predictive maintenance provided by the MGDTs, the MGs resilience can be noticeably improved and the system/asset lifetime can be extended. Accordingly, the MGDTs will reduce the operation cost, improve the performance of the underlying physical systems, and enhance the sustainability of the MGs. Although

many kinds of research have been conducted during the recent years, digital twinning in MGs is still in its infancy and a long way must be paved to take full advantage of its promise.

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**NAJMEH BAZMOHAMMADI** (Member, IEEE) received the B.Sc. degree in electrical engineering and the M.Sc. degree in electrical engineering (control theory) from the Ferdowsi University of Mashhad, Iran, in 2009 and 2012, respectively, and the Ph.D. degree in electrical engineering (control theory) from the K. N. Toosi University of Technology, Tehran, Iran, in 2019. She is currently a Postdoctoral Fellow with the Center for Research on Microgrids (CROM), AAU Energy, Aalborg University, Denmark. Her current research interests include digital twins, modeling and control of dynamic systems, optimization, model predictive control, and its application in energy management of hybrid and renewable-based power systems and life support systems.

**AHMAD MADARY** received the B.Sc. degree in mechanical engineering from the Iran University of Science and Technology and the M.Sc. degree in mechanical engineering (applied design) from Shiraz University, Iran, in 2009 and 2013, respectively, and the Ph.D. degree in electrical engineering (control theory) from Tarbiat Modares University, in 2021. He was a Visiting Researcher at the Computer Science Department, Aalborg University, Denmark, in 2018. He is currently a Technical Assistant with the Department of Mechanical and Production Engineering, Aarhus University, Denmark. His research interests include robotics (parallel and serial robotic manipulators), modeling, control, and safety of dynamical systems, system identification, mechatronics, hybrid systems, embedded controllers, and microcontrollers.

**JUAN C. VASQUEZ** (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees from UAM, Colombia, and the Ph.D. degree from UPC, Spain. In 2019, he became a Professor in energy internet and microgrids. Currently, he is the Co-Director of the Villum Center for Research on Microgrids. He has published more than 450 journal articles, which have been cited more than 19000 times. His research interests include operation, control, energy management applied to AC/DC microgrids, and the integration of the IoT, energy internet, digital twin, and blockchain solutions. He has been a Highly Cited Researcher, since 2017, and was a recipient of the Young Investigator Award, in 2019.

**HAMID BAZ MOHAMMADI** received the bachelor's degree in electrical engineering and the Master of Management degree in artificial intelligence. He is currently a Senior Mobile Network Optimization Engineer and a Data Scientist with TELUS Mobility, Canada. Before joining TELUS in 2017, he had worked with Huawei and Ericsson for 11 years. His past 15 years of experience include the design and optimization of different generations of mobile networks (2G to 5G), technical teams leadership, and building AI-based models to analyze the performance of the networks. In his AI experience, he has contributed to several AI projects inside and outside of the mobile networks domain, with a focus on anomaly detection in geographically distributed timeseries data.

**BASEEM KHAN** (Senior Member, IEEE) received the B.Eng. degree in electrical engineering from Rajiv Gandhi Technological University, Bhopal, India, in 2008, and the M.Tech. and D.Phil. degrees in electrical engineering from the Maulana Azad National Institute of Technology, Bhopal, India, in 2010 and 2014, respectively. He is currently working as a Faculty Member at Hawassa University, Ethiopia. He has published more than 100 research papers in well reputable research journals, including IEEE Transactions, IEEE Access, *Computer and Electrical Engineering* (Elsevier), *IET GTD*, *IET PRG*, and *IET Power Electronics*. Furthermore, he has published, authored, and edited books with Wiley, CRC Press, and Elsevier. His research interests include power system restructuring, power system planning, smart grid technologies, meta-heuristic optimization techniques, reliability analysis of renewable energy systems, power quality analysis, and renewable energy integration.

**YING WU** received the Ph.D. degree from Northwestern Polytechnical University, China, in 2014. From 2006 to 2011, she was a Software Engineer engaged in the research and development of interactive system architecture and large-scale complex network systems with the Hewlett-Packard Global Research and Development Center, Shanghai, China. She is currently an Associate Professor at Xi'an Shiyou University, China, and a Postdoctoral Fellow with the Center for Research on Microgrids (CROM), AAU Energy, Aalborg University, Denmark. Her research interests include the digitalization and distributed control of networked energy systems, the Internet-of-Things-based microgrid architecture, and communication and control in the energy internet.

**JOSEP M. GUERRERO** (Fellow, IEEE) received the B.Sc. degree in telecommunications engineering, the M.Sc. degree in electronics engineering, and the Ph.D. degree from the Technical University of Catalonia, Barcelona, in 1997, 2000, and 2003, respectively. Since 2011, he has been a Full Professor with the Department of AAU Energy, Aalborg University, Denmark. In 2019, he became a Villum Investigator by the Villum Fonden, which supports the Center for Research on Microgrids (CROM), Aalborg University. His research interests include oriented to different microgrid aspects, including applications as remote communities, energy prosumers, and maritime and space microgrids.

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