Intelligent Distributed Cyber-Physical Systems for Renewable Energy Communities

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The Internet of Things (IoT) is transforming various domains, including smart energy management, by enabling the integration of complex digital and physical components in distributed cyber-physical systems (DCPSs). The design of DCPSs has so far been focused on performance-related, non-functional requirements.

renewable energy communities (RECs) | energy-aware DCPS | edge-to-cloud infrastructure | deep learning | heirarchical-CPS

1. Introduction

The Internet of Things (IoT) has become increasingly prevalent across various application domains, such as smart cities and Industry 4.0, leading to a heightened emphasis on the design and development of distributed cyber-physical systems (DCPSs). These systems' behavior is significantly influenced by their context, encompassing the external physical environment and the internal states of the IT components and networked infrastructure. In recent years, DCPSs have been proposed to facilitate renewable energy communities (RECs), which promote sustainable development within local communities by adopting renewable energy sources. RECs consist of individuals, organizations, and businesses collaborating to produce and consume renewable energy, such as solar or wind power. Integrating DCPSs in RECs can enhance energy usage efficiency by monitoring and controlling energy flow within the community. DCPSs provide the essential infrastructure for RECs to supervise and regulate the production and consumption of renewable energy sources. In this context, IoT devices collect energy production and consumption data, which is then analyzed by cloud-based platforms to optimize the energy management system. By harnessing these technologies, RECs can establish a more decentralized and democratized energy system, empowering local communities to manage their energy resources actively. Numerous global initiatives have successfully integrated DCPSs and RECs. For example, in Germany, the "EnergieWendeBauen" project (energiewendebauen.de, accessed on 1 March 2023) has implemented a DCPS-based platform for energy management in residential communities. This platform enables residents to monitor and control their energy usage and share excess renewable energy within the community. Similarly, the "Solar Share" project in Italy (lifegate.it, accessed on 1 March 2023)has introduced a DCPS-based platform that allows individuals and small businesses to share surplus solar energy with their neighbors. Integrating DCPSs and RECs offers a promising opportunity to promote sustainable development and transform the energy landscape. By leveraging the power of IoT and cloud computing technologies, these systems can enable more efficient, sustainable, and decentralized energy management. Future research in this area should focus on developing scalable and secure DCPS-based platforms to support the widespread adoption of renewable energy sources in local communities worldwide.

To enable the creation of DCPSs, an overlay-based distinction between the physical environment and the digital infrastructure is considered a cornerstone of the whole scenario. IoT devices' sensing and actuation capabilities facilitate this interaction between the two layers, which collect data to send to the cloud for processing according to various scopes, such as latency reduction, privacy-preserving, or security purposes. Data processing in the cloud typically involves logic units adapting their models based on observed data and providing dynamic and queryable run time models for a pipeline of services. Until now, the design of DCPSs has primarily focused on performance-related, non-functional requirements. However, sustainability has become critical due to the growing power consumption and associated computing expenses at different levels in these systems. The increasing sophistication of DCPSs requires more computational resources, which leads to increased energy costs. To address the sustainability challenge, integrating energy-aware digital components in DCPSs is an essential activity to create sustainable systems where IoT devices and server-based infrastructures can make autonomous decisions based on the outcomes of self-learning algorithms. DCPSs are becoming increasingly complex and consist of multiple interacting subsystems and environments. The aggregation of subsystems occurs at different levels, from edge devices to large systems. The proposed solution envisions a future where DCPSs are treated as conscious systems that can respond to internal and external triggers and adapt their operations to achieve predefined goals. These systems will be able to learn from experience through self-learning mechanisms and carry out planned actions and predictive strategies at the overall system level to optimize resources, maximize efficiency, and reduce energy costs.

A renewable energy community realized upon a DCPS is an environment in which two aspects must be combined and orchestrated: energy production and energy consumption. The trade-off has to be realized not only in terms of online orchestration but also by considering historical data related to the two aspects mentioned above. From this perspective, IoT devices are essential to observe physical parameters, such as current consumption and voltage. A distributed infrastructure collects and processes these samples through optimizing self-learning algorithms.

2. A Deep Learning-Driven Self-Conscious Distributed Cyber-Physical System for Renewable Energy Communities

Distributed cyber-physical systems (DCPSs) can significantly benefit from recent advancements in distributed computing, including architectural elements, algorithms, and models. In [1], the authors highlight key challenges associated with DCPSs, such as latency, energy consumption, security/privacy, and reliability. Designing a reliable IoT communication infrastructure for DCPSs remains an open challenge, as other researchers in [2][3] emphasized. Meanwhile, ref. [4] formulates the scheduling computation on the cloud continuum as a mixed-integer linear programming problem and proposes an energy-aware deployment and replication scheduling model, considering the capability of edge/fog nodes to harvest "green" energy.

The increased adoption of DCPSs, combined with the need to address emerging climate change issues, has led to renewable energy communities (RECs). In recent years, energy delivery and consumption in DCPSs have gained particular attention due to the increasing number of users (producers and consumers) involved in generating and sharing renewable energy [5][6]. Research on energy management and optimization through energy exchange, sharing, and storage mechanisms, along with the characterization of user behaviours, is crucial for achieving sustainability in RECs [7][8][9]. In this context, ref. [10] proposes a distributed energy management system (EMS) for optimal microgrid operation, considering power distribution constraints. The EMS demonstrates effectiveness in both islanded and grid-connected modes, with future work focusing on its implementation in real systems and performance analysis. Cloud computing has emerged as a popular solution for managing, storing, and processing data in energy systems. As outlined by [11], it offers a scalable, on-demand, and cost-effective model for delivering IT resources via the Internet. Numerous researchers have investigated the application of cloud computing for energy management and optimization. In [12], the authors explore the new challenges that smart grid technology introduces for comprehensive data management and examine how cloud computing can address these issues. Their survey encompasses smart grid and energy management methods, investigating the use of cloud computing in various domains, such as energy management, demand-side management, building energy management, energy hubs, and power dispatching systems.

Smart grids represent a modernized electrical grid infrastructure that employs cutting-edge technologies to monitor, control, and optimize electrical power generation, distribution, and consumption. The authors in [13] present a detailed overview of smart grid technologies, including advanced metering infrastructure, demand response, and distributed energy resources. Furthermore, ref. [14] reviews demand-side management techniques in smart grids, emphasizing the importance of load forecasting, demand response, and energy storage systems in achieving energy efficiency and grid reliability. Integrating the Internet of Things (IoT) and cloud computing has shown immense potential in enhancing the efficiency of energy management systems. IoT provides a platform for connecting and collecting data from various devices and sensors, while cloud computing enables the processing and analysis of these data. In [15], the authors discuss how incorporating IoT technologies into smart grids can improve monitoring, communication, and data processing across various devices. They propose a layered approach for classifying IoT applications in smart grids and explore recent research efforts along with future directions. On the other hand, the authors in [16] investigate the benefits of combining IoT and cloud computing for smart grid applications, particularly in demand response, fault detection, and renewable energy integration. This synergistic approach holds promise for further energy management and optimization advancements, paving the way for more sustainable and efficient energy systems. Ref. [17] investigates the correlation between solar irradiance and harmonic distortion in grid-tied photovoltaic distributed energy resource (PV-DERs) systems. Understanding this relationship can help develop effective grid-to-grid power-sharing arrangements and mitigate harmonics in bidirectional power-transfer community-grid structures.

The self-management processes that govern the operation of RECs are based on machine learning (ML) techniques to improve their effectiveness, autonomy, and efficiency. Energy demand and supply forecasting, self-consumption, characterization of power consumption behaviours, efficient scheduling of energy resources, and appliance obsolescence are some tasks involving ML and deep learning (DL) techniques [18][19][20][21].

Some studies have been conducted using both statistical approaches [22][23][24] and ML models for predicting individual household loads, predominantly the latter, due to their ability to capture complex patterns in the data and provide accurate predictions [25][26][27][28]. On the other hand, despite other works that have been conducted to improve the accuracy of household load forecasting using the advantages of DL models, and thus of the use of the neural network (NN)-based algorithms [29][30][31], other investigations have focused on improving the accuracy of household load forecasting by taking advantage of DL architectures for time series prediction, including the highly effective long short-term memory neural networks (LSTMs) [32][33]. The latter have demonstrated remarkable advancements in recent times, despite the volatility of predictions caused by the heterogeneity and randomness of household behavior; however, they are out-performed by the more accurate Bi-LSTM networks [34][35][36]. In this context, modeling user profiles to meet energy demand while optimizing overall consumption is crucial [37]. Thus, DL models are a must to identify users' lifestyles based on their daily energy consumption. In addition, the meteorological forecast data must also be considered when modeling energy profiles, as renewable energy sources are often intermittent. Research on developing planning strategies for smart load distribution and integrating renewable energy resources is ongoing, and federated learning (FL) approaches are being investigated for this purpose [38][39].

Energy awareness must be incorporated at every layer (models, data, algorithms, hardware components, etc.) and tier (cloud, edge/fog, IoT) of the IT infrastructure of DCPSs, and in every phase (design, deployment, execution, etc.). To address this problem, the scientific community has begun to define methodologies and approaches to evaluate the energy consumption of models and algorithms based on structural and behavioural parameters [40]. For example, ref. [41] proposes an energy-efficient IoT data compression algorithm to optimize the execution of ML algorithms at the edge. At the same time, ref. [42][43] focuses on the energy optimization of the deployment and distributed training of ML models at the edge, respectively. The processing capabilities of IoT devices represent both a resource and a constraint. Thus, designing a suitable infrastructure is both a requirement and a challenge. The trend towards offloading data analytics tasks from edge devices to the cloud has been increasing. However, existing offloading approaches face the challenge of being static and needing help to adjust to changing workloads and network conditions.

Moreover, in [44], an energy-aware workload allocation framework for distributed deep neural networks (DNNs) in the edge-cloud continuum was presented to minimize energy costs for inference. This framework considers energy consumption and computation performance to optimize the allocation of workloads in a distributed computing environment. Offloading data analytics tasks from edge devices to the cloud has great potential for improving the efficiency and performance of DCPSs. However, existing offloading approaches have limitations, and researchers continue to develop more dynamic and energy-efficient solutions to overcome these challenges.

The advancements in DCPS research make significant progress on latency, energy consumption, security/privacy, reliability, and computation allocation challenges, improving their effectiveness, autonomy, and efficiency while contributing to sustainability and addressing emerging problems related to climate change. For these reasons, the solution proposed in this research aims to define an optimal implementation/architecture of an energy-aware DCPS, providing a smart and flexible power system while enabling the integration of renewable energy sources and facilitating the integration of microgrids and other distributed energy resources. Ref. [45] presents an asymmetrical single-phase eleven-level inverter for the grid integration of distributed power generation sources, contributing to improved power quality and cost-effectiveness in grid-connected systems. Moreover, ref. [46] introduces a distributed-variable flow-variable temperature (VF-VT) approach for integrated energy and heating systems, offering privacy preservation, feasibility, and scalability. The study identifies future research directions, including global optimization, model development, and improved thermal dynamics modeling, which can further enhance the performance and efficiency of energy-aware DCPSs.

Researchers proposed solution employs a combined approach for managing both the production and consumption aspects of RECs, which sets it apart from other systems. In addition to this comprehensive approach, their solution provides three key contributions that, although present in some existing solutions, are not typically found together in a single framework. Specifically, their approach integrates all three contributions, enhancing the overall effectiveness and efficiency of the system. In comparison, the papers from references [18][19][20][21][22][23][24][25][26][27][28][29][30][31][32][33][34][35][36][37] primarily focus on applying AI techniques to individual households rather than entire communities. While these studies offer valuable insights into AI-based energy management, they may not fully capture the complexity and interconnectedness of energy production and consumption in broader communities. By addressing energy management at the community level, their solution aims to achieve a more comprehensive understanding and optimization of energy distribution and utilization in RECs. Moreover, the works from references [5][6][7][8][9] do not explicitly mention the use of AI techniques in their proposed solutions. Although these studies contribute to advancing energy-aware DCPSs, they may not fully leverage the potential of AI and ML in improving energy management, forecasting, and optimization in RECs. By incorporating AI and, more specifically, DL techniques in researchers' solution, they seek to further enhance the performance, efficiency, and adaptability of their proposed energy-aware DCPS architecture.

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