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Editorial

The Journey Towards the Energy Transition: Perspectives from the International Conference on Environment and Electrical Engineering (EEEIC)

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Over the past decade, decarbonization and environmental issues have taken a key role in worldwide politics. In particular, the European Union (EU) declared its strong commitment to take the lead in the energy transition process. European policymakers aim at a low-carbon future and reduction of greenhouse gas emissions. After the Paris Agreement, the European Commission started a significant review of the European energy regulatory framework to accelerate the transition from fossil fuels to clean energy, promoting renewable energy as one of the pillars of a decarbonized energy system. In 2019, the European Commission finalized the "Clean Energy for all Europeans Package" (CEP), a framework of eight legislative acts that shape the EU energy policies, establishing a 40% reduction in greenhouse gas emissions and a 32.5% improvement in energy efficiency as targets for 2030.

In this context, it should be noted that most of the European buildings are multi-unit buildings, responsible for 40% of the whole energy consumption. The European Commission set as a target that about 50% of buildings' energy demand should be covered by Renewable Energy Sources (RESs). The aggregation of users into Renewable Energy Communities (RECs) represents an efficient solution toward this goal. The European Directive 2018/2001—also known as Renewable Energy Directive (RED II)—represents a fundamental step for the clean energy transition since it recognizes Energy Communities (ECs) at the European level.

The IEEE International Conference on Environment and Electrical Engineering (EEEIC) welcomes and encourages research activities from this perspective. The present editorial reviews the most significant contributions published in the special issue of MDPI *Energies*, "Selected Papers from 20th IEEE International Conference on Environment and Electrical Engineering (EEEIC 2020)".

Besides economic and political interests involved in energy production from conventional sources, the actual scarce availability of fossil fuels and the environmental impact of energy produced by non-RESs have endorsed more focused attention on polluting agents and clean energy, yet helping broaden the horizons towards measures favoring better life quality and working conditions for the workers. In ref. [1], solar radiance sensors were employed to estimate the levels of occupational irradiance for open-air workers. The study, revealing dangerous exposure levels, was conducted with a population of three workers in Italy, equipped with personal dosimeters to monitor UVA and UVB/C irradiance for 23 working days.

In this complex transitional context, a key factor is represented by data gathering and management to predict energy production and consumption and prevent power plants' reduced performance by detecting inefficiencies and abnormal operating conditions. Thermographic non-destructive tests (TNDTs) are employed to detect soiling, debris, and dust, causing a reduction in the solar radiation reaching the PV cells, and hot spots,

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impairing efficient energy production. Convolutional neural network (CNN) methods are employed to classify the gathered thermal images after pre-processing. A comprehensive comparison of different configurations of CNN algorithms (including a different number of convolutional layers, epochs, optimizers, etc.) was carried out in ref. [2] as to the accuracy achieved in the binary classification of anomalies into the 'dust' or 'fault' type. Although displaying the same 98% accuracy of the CNN with augmentation, results obtained by CNN without augmentation present a lower standard deviation, suggesting superior stability of the latter method.

CNN was recognized in ref. [3] as one of the most used and capable data-driven models for classification-oriented data mining when assessing Knowledge Discovery in a large Database (KDD). Whether the goal consists of prediction or description from massive data sets made available by meters pervasively installed in the distribution network (e.g., SCADA systems, AMI, PMU, etc.), the authors of ref. [3] envision in KDD a successful methodology to extract actual information for the development of decision support systems for distribution system operators. A method was proposed for load prediction with different forecasting horizons, and implemented in a case study involving active power prediction within 2, 6, and 12 h. The combinations of Minimum Redundancy Maximum Relevancy (MRMR), for features selection and management of the large cardinality of the problem, with lazy learning and random forest regression as machine learning algorithms revealed to be the most accurate.

The concept of energy transition also translates into strategies for demand-side management and optimization of energy production from RESs.

Regarding the former strategy, load shifting was exploited in ref. [4] to minimize energy expenses of an industrial laundry while accounting for the following aspects: variability of energy tariffs (single, double, dynamic tariff pricing, with or without incentives); demand response programs (i.e., compliance to upper limits of energy absorption, as established by the grid operator); owner preferences and necessities; working cycle duration and possible constraints on the operational sequence of different devices (which depend on the task performed by each device in the overall industrial process). The minimization of the defined cost function in different scenarios, assessed by means of mixed integer linear programming, revealed that incentives are needed to support the flexible energy consumption of industrial sites. Indeed, grid-side constraints may cause the load to be shifted to periods with raising energy prices charged to the user.

As to optimization of production from RESs, more and more advanced control algorithms are being developed to increase efficiency in transforming solar to electrical energy. An innovative architecture for Maximum Power Point Tracking (MPPT) for PV systems was proposed in ref. [5] to reduce steady-state error and high-frequency oscillations of the panel voltage around the target value from the MPPT. Traditional controls combine Perturb and Observe (P&O) techniques for voltage reference production and PID controllers, resulting in an undesired chattering effect. The authors proposed an Adaptive Sliding Mode Controller (ASMC) in conjunction with the Improved Pattern Search Method (IPSM) to track the maximum power working point of the PV plant. The performance of different MPPT algorithms (P&O, PSO, and IPSM) in combination with PID controller or ASMC was evaluated; the proposed IPSM-ASMC provided promising results, displaying reduced chattering, yet increased MPP computational time.

The less energy-intensive P&O algorithm was chosen in ref. [6] to optimize the output power of a novel low-power wind-energy harvester: the Fluttering Energy Harvester for Autonomous Powering (FLEHAP). The system consists of a MicroController Unit (MCU), a rectifier, a DC/DC Buck-Boost Converter, a DC/DC boost converter, a storage unit, and an auxiliary circuit. The MCU verifies the input power and runs the MPPT algorithm. The harvested power in this low-power application is in the order of magnitude of that consumed by control circuits.

Instead, a Second Order Sliding Mode Control (SOSMC) was applied in ref. [7] to improve the effectiveness of the drive system, decrease the level of Total Harmonic Distortion

(THD), and reduce the chattering phenomenon for applications involving asynchronous, permanent magnet motor (PMSM). The PMSM is fed by a Direct Matrix Converter (DMC), i.e., an AC–AC converter where bidirectional switches allow operation in four quadrants, bidirectional power flow, and adjustable power factor. The DMC, linked to the grid by means of a passive filter, reduces the THD. A comparative study between the conventional SMC and SOSMC was conducted, showing the proposed control's improvements in chattering attenuation and reduction of harmonic distortion rate.

Due to the increasing penetration of distributed RESs at lower voltage levels, new technical challenges must be faced by operating grids, originally designed to guarantee the quality of voltage supplied to user-only nodes. Power injection by RESs into the low-voltage grid has contributed to causing the violation of the allowed variability ranges for node voltages (3%–5% of the nominal value), depending on the instantaneous unbalance between production and load. Two scenarios were assessed in ref. [8] regarding different installed roof PV capacities connected to a German low voltage grid. To ensure the voltage quality requirements, grid supporting solutions were identified in node-connected batteries and grid reinforcement actions (e.g., sizing and installing additional cables connected to the most stressed grid nodes). An optimization algorithm based on linearized load flow was implemented for optimal location and sizing of batteries, while a heuristic algorithm was adopted for grid reinforcement interventions. Both approaches aim at minimizing the cost of the adopted solution, although the latter method may get stuck in local minima. Results revealed battery installation to be more convenient, although they might be partially biased by neglecting widely variable maintenance expenses for both solutions.

Practical applications rely on batteries as functional electrochemical harvesting devices for the grid's service and electric transportation systems. In fact, 23% of polluting, highly environmentally impacting emissions are attributed to the transportation sector, encouraging the spread of Electric Hybrid Vehicles (EHVs) and Electric Vehicles (EVs). The authors of ref. [9] proposed an event-driven Coulomb counting method to estimate lithium-ion battery state of charge (SOC) for EVs applications. An event-driven sampling at a variable frequency and specific choices for quantization (uniform or non-uniform) of the expected range of variation of measured voltage and current allow a relevant gain in processing gathered data for SOC estimation and calibration. The simplification, consisting of the reduction of required samples to be handled (compared to traditional sampling at the constant frequency), computational cost, and hardware complexity, is introduced at the price of increased error in the SOC estimation (although still below the 5%) for the illustrated application case.

The EVs market has grown considerably in recent years, even due to incentive policies. The high penetration of EVs obviously affects the energy demand from power grids. In ref. [10], the authors proposed an innovative estimation model of the total energy consumption of EVs for different driving conditions. That would allow scheduling power generation to avoid disturbances at the network level. Estimating the total energy demand of EVs involves a large amount of data, such as temperature, driving speed, traffic, and covered distance. Even though the proposed algorithm is developed in Python, exploiting Big Data techniques, some parts of data manipulation and visualization are conducted in KNIME. The model is applied to real-world datasets: taxies trajectories and weather conditions of New York City, as well as EVs datasets. The study was carried out by replacing each taxi with an EV whose characteristics are well-known; EVs are initially provided with new batteries with 100% SOC, which are assumed not to lose capacity after multiple charge cycles. The analysis showed the energy consumption for each month of 2018 and during the weekdays, providing demand patterns at any time interval. In this way, it is possible to foresee measures to balance power generation and consumption, preventing the simultaneous charging of a large number of EVs.

European documents [11,12] underline that traction energy consumption in electric public transport plays a significant role in decreasing greenhouse gas emissions and air pollutants. The authors of ref. [13] proposed a model acting on metro lines' driving speed profiles to reduce their energy demand. An eco-driving strategy may be quickly adopted on current trains with low investments because the railway infrastructure does not require any intervention. The proposed method was applied to the Metro in Naples, Italy. The traction energy consumption depends on the travel time and train cruising speed. These variables are linked by a function that must be calibrated for each section of the Metro line, taking into account the performance of the rolling stock and the actual curvature and elevation track profile. The authors solved the optimization problem through two different approaches: the first is based on a Generalised Reduced Gradient (GRG) algorithm; the second exploits a discrete simulation model built in Arena software by means of the module Optquest. Simulation results showed that both approaches lead to energy savings of around 25% just working on driving behavior.

Notwithstanding the above, EVs could affect the environment depending on the nature of electricity used to charge them. The study in ref. [14] aimed to evaluate electric mobility's economic and environmental sustainability using the Life Cycle Thinking (LCT) methodology. The energy efficiency of battery EVs is higher than conventional vehicles, but only if charged with energy produced by RESs. In addition, the literature reports that the CO_2 eq emissions per kWh of battery capacity depend on the battery typology but also on the Life Cycle Assessment (LCA) methodology involved. However, EVs present a lower carbon footprint than conventional vehicles. In this analysis, the LCT methodology exploited two approaches: the LCA and the Life Cycle Cost (LCC). In the LCA, all data related to energy production from November 2019 to January 2020 have been collected. Thus, the environmental impact of the electricity sources has been assessed by using the software SimaPro 8.5: various midpoint methods have been applied and compared, i.e., ReCiPe 2016, ILCD 2011, CML-IA, IMPACT 2002+ and EPD(2013). Cumulative Energy Demand (CED) is a widely applied tool for analyzing the energy used during the life cycle of a good or a service, yet, integration with other impact assessment methods, such as ReCiPe 2016 or ILCD 2011, is recommended. The LCC evaluation defines the total cost of products and services, considering their entire life cycle.

The European Union defined, for 2030 and 2050, several targets for a clean energy transition which may be reached just with a high penetration of RESs. As seen above, the integration of renewable energy plants into the power grid is affected by several challenges, such as upgrading the grid infrastructure and optimizing and managing the available energy. In this scenario, the authors of this editorial want to raise awareness of these issues among researchers.

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