Artificial Intelligence Assisted Smart Photovoltaics

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Abstract

The paper discusses research efforts in combining recent progress in Artificial Intelligence with automated management of solar energy generated in grid-connected photovoltaic (PV) systems along with their operation-and-maintenance (O&M) and their smart on-grid integration control. The outlined research aligns with the strategy of the European Union joining Digital and Green agendas as two major pillars for the COVID-19 economic recovery in the EU and is a part of the EU funded standardization action under the H2020 StandICT programme coordinated by the author and hosted by the Smart Energy Standards Group of the European Information Technologies Certification Institute (EITCI SESG) in cooperation with the European Solar Network. It also contributes to one of the four primary objectives of the European Green Deal, i.e. to achieve a fully integrated, interconnected and digitalized EU energy market by increasing research oriented towards technical reference standardization aimed at consolidation of the expert community and the technology uptake.

Keywords: Smart PV, AI, Photovoltaics, Smart grids, Smart metering, Smart energy, MPPT, Standardization

1. Introduction

A grid-connected PV system is generating electricity from the solar irradiation while being interconnected to the utility electric power grid. It generally consists of solar panels (PV modules), inverters, power conditioning units and grid connection equipment. Such PV systems range from small residential and commercial rooftop installations to large industrial-scale solar power-plants. Unlike stand-alone (off-grid) PV power systems, a grid-connected system does not have to include integrated batteries. Thus whenever the solar irradiation conditions admit it, the grid-connected PV system automatically supplies the excess power beyond consumption by the connected load, to the utility electric grid, turning a consumer into a prosumer, thus transforming the energy market to a highly distributed model and introducing a dual concept of Distributed / Renewable Energy Sources (DES/RES). Increasing automation of the PV solar power generated in-grid feeding control, operative optimization and maintenance has been recently dubbed smart PV, although in terms of in-grid feeding control it is mainly based on the developments of the smart grid achievements. The paper studies progress on research results in this area enabling undertaking and advancing international standardization efforts regarding PV systems grid-integration, as well as pronounces the need for extending these technical reference standards towards Artificial Intelligence assisted smart control over PV systems in solar power plants, PV integrated industrial buildings and the prosumer residential homes PV installations. A progress towards AI assisted smart PV systems in Deep Machine Learning and Neural Network models trained on a feedback loop of operational parameters for O&M and the in-grid (smart grid) power feeding is expected to contribute to increasing the solar energy uptake rates in parallel to continuously impressive PV modules efficiency-to-cost ratios growth.

2. AI assisted smart PV modules research and standardization

Magnitude of various PV modules and inverters equipment producers develop their own systems of automated O&M and control processes. Many solar modules producers embed electronics into PV modules. Such systems (smart modules) enable maximum power point tracking (MPPT) along with monitoring of performance data for fault detection at a module level (cf. Dhoke, 2019). Some of these systems make use of power optimizers to maximize generated power outputs. With recent PV advancements the related electronics with a proper analytical software can compensate e.g. for shadows falling partially on a section of a solar module causing drop of electrical output of one or more strings of cells, but not zeroing the output of the entire module. A smart PV system should automatically control all its sophisticated operation parameters, including central or module-level MPPT, discover, diagnose and neutralize faults, hence improving its total efficiency, lowering

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O&M costs and increasing revenues. Main features of smart PV systems are automation, digitization and intelligence, optimally based on latest developments in AI applications (neural-networks big data learning comprising constant feedback input of all operational parameters of PV systems and their on-grid interconnection to AI enabled management system). The presented research aims at supporting international standardization efforts at a higher level of abstraction for the state of the art framework standard for deep-learning NN AI assisted smart control over PV systems in solar power plants, PV integrated industrial buildings and the prosumer residential homes PV installations. Under the StandICT H2020 supported effort, researched multitudes of possible solutions and architectures are currently evaluated in order to propose a European framework of Smart PV reference standards under a newly organized Standards Developing Workgroup hosted by the European IT Certification Institute jointly with the European Solar Network. The project is tasked by the StandICT programme to conceive 2 Request for Comments standards drafts that will be iterated among WG experts and disseminated to other international SDOs active in the area of Smart Grids and Smart Metering standards with a focus on the solar power. The newly proposed Smart PV standard aims at systemizing conceptual architecture and implementation specification to define compatibility requirements between interfaces of PV modules and their associated electronic equipment control systems with inclusion of AI and cloud technologies. It aims in filling gaps in general smart-grid uniform communication standards mainly pursued by international SDOs in this field. The relevance of this research and standardization effort is in a direct correspondence with the EU Rolling-Plan 2020 for smart energy standardization overviewing the needs for digital standards in support of the EU policy for Smart Grids and Smart Metering in focus on the PV solar energy. Accordingly with the EU Rolling-Plan 2020 ICT standards in energy are expected to cover smart grid management, grid-balancing and interfacing with millions of new renewable sources in particular optimizing efficiency in complex processes of renewable energy systems control. These standards mainly focus on uniform communication and cybersecurity protocols (providing plug & play compatibility for new devices entering the grid, from renewable sources to electric cars or other smart devices and IoT enhancing smart homes, buildings or cities of the future). The current dynamic EU energy transformation is driven by two main factors: the energy systems becoming clean (i.e. environmentally neutral accordingly with goals of the EU climate and energy framework and the European Green Deal strategy of the European Commission) based on renewable and consumer-centric sources, primarily in a form of the solar power, and the ongoing digital/smart transformation of the energy and electrical grid sectors. The first factor is due to the EU energy policy encouraging stakeholders to adapt to an increasing number of means of generating electricity from a variety of renewable energy sources with minimizing environmental impact (clean energy transformation). The key policy milestones for this transformation are the EU's energy and climate targets for 2030 which emphasize Europe's leading role in the global fight against climate change. These 2030 EU climate and energy framework targets include at least 40% EU domestic reduction in greenhouse gas emissions compared to 1990 (with an increased ambition to 55% reduction as a part of the European Green Deal of September 2020), at least 32% share of renewable energy consumed in the EU, at least 32,5% improvement of energy efficiency and an electricity interconnection targeted at 15%. In this context both the PV systems and the electricity networks are of key importance. In 2012 electricity represented 22% of the EU's energy consumption with renewables accounting for a share of 24% of gross production (with ca. 3% increase on 2011, while reaching as high as 30.2% in 2016 and expected to grow up to 55% in 2030, correspondingly with the 2030 energy and climate goals and the Paris Agreement). As 2020 marked a hallmark achievement in the EU (cf. Rządkowska, A., October 2020) – for the first time the electricity generation mix has been dominated by renewables (at 39% share, exceeding by 4% the combined fossil fuels at 36% of electricity generation – as confirmed by the Directorate-General for Energy of the European Commission Communication of 9th April 2021) and the solar energy steadily increasing its stake (to 5.2% on the EU-27 level, and almost up to 10% in Italy, Greece, Germany and Spain), the smart PV based contribution to its efficiency is becoming even more so important. Furthermore the consumer position in the energy value chain has considerably changed. The energy consumer can now easily become a prosumer, deploying grid-connected renewable energy source (e.g. a PV system DES/RES), feeding the surplus of the generated energy into the utility grid. For this end with smart optimization of energy efficiency the digital and energy technologies need to overlap taking advantage of most recent developments in big data enabled AI control methods, smart homes and cities applications, energy intelligent products, the IoT, 5G networks, etc. It is for a reason that the EU COVID-19 strategic response is summarized in prioritizing two pillars: the single energy market and the digital single market combined as strongly interdependent and being both critical to the policy of the EU. This is where the second factor of EU energy transformation through smart (AI assisted) digitization is pronounced, with digital and AI holding a potential to further support uptake of the solar power. Discussed efforts target a specific sector of this outlined in-demand technical standards of smart PV systems assisted by feedback loop trained neural networks based AI. An important concept for the proposed standards is defining a common cloud-based platform specification for distributed Smart PV operational data aggregation that will enable NN deep-learning not only on individual operative systems but also on the whole ecosystem of AI enabled PV devices (with properly addressed security and privacy issues).

3. Current progress in smart energy and smart grids standardization

Initiatives at standardizing concepts and technological approaches in leveraging AI methods to enable development of disruptive solutions in PV value chain, forming cooperative relations between individual experts in both fields of AI and solar energy, as well as scaling this cooperation to the level of institutional partnerships of research and industry stakeholders, will certainly speed uptake of the AI assisted smart PV. Stakeholders of potential interest in this regard (beyond international Standards Developing Organizations) include PV systems producers (from designs to manufacturing of single solar cells up to integration of solar modules and electronic systems), PV integrators and deployments companies, operators or owners of PV power plants, as well as AI and PV industrial experts and researchers can cooperate exchanging supplied necessary data and solar subject matter expertise with AI and ML expertise. The general goal of AI assisted PV technology is in improving economic feasibility of the PV energy transition (e.g. by cost optimization of deployments and operations of solar modules), as well as increasing reliability and value of solar PV technologies upon their integration with advancing smart grids, enabling a shift of the energy market from a centralized model to a distributed one, with inclusion of prosumers in PV solar power enabled microgeneration. AI and ML hold a potential to tackle emerging challenges for the PV wide scale adoption. Naturally an ongoing identification of new applications advancing early-stage AI assisted PV technology will be taking place and the current initial standard drafting aims at tidying up technical directions of currently known applications and classifying many various approaches. The current initiation of a general level reference standard will be further iterated towards more mature and advanced technical reference standard, and to this the AI Smart PV group under the Smart Energy Standardization Group of the EITCI Institute has been established. These AI assisted smart PV standardization efforts are contextualized in following preceding initiatives. In October of 2014 the CEN/CENELEC/ETSI's Smart Grid Coordination Group (SG-CG) successfully completed requirements of the EC M/490 mandate, with industry representatives confirming their will to take over and implement the results of the Expert-Group-1 work on the first iteration of the Smart Grid standards. Consequently, EG1 of the Smart Grids Task Force assessed in 2016 the interoperability, standards and functionalities applied in the large scale roll out of smart-energy metering in Member States and in particular the status of implementation of the required standardized interfaces, along with EC recommended functionalities related to the provision of information to consumers (summarizing report was published in October of 2015). Further coordination of standardization efforts related to Smart Meters was due to the Smart Meters Coordination Group (SM-CG) established under the M/441 mandate. The SM-CG has returned the reference architecture (TR-50572) and an overview of technical requirements, continuing to liaise with its successor CG-SEG (since end of 2016, the CEN-CENELEC-ETSI Smart Energy Grid Coordination Group took over and cooperates with the EC-SGTF). In September 2017 EC issued a proposal for a regulation on ENISA on Cybersecurity certification (Cybersecurity Act) as a voluntary mechanism framework enabling creation of individual EU-wide certification schemes (with a scheme indicating a specific product/service, an assurance level and a standard for evaluation). Such schemes are now developed to verify security properties of digital energy systems. The EC fostered conceiving a common interoperability language SAREF - a standard of ETSI and OneM2M. The CEN-CENELEC-ETSI is endowed to further align SAREF with the data models developed at ISO and IEC. These are initial steps to enable smart-energy grid and its adaptive demand-response operation mode. The standards of the discussed research will mainly provide an added value as extensions of the CENELEC / IEC-TC CLC/TC-82 (Solar photovoltaic energy systems) and the CLC/TC-57 (Power systems management and associated information exchange) for power systems control equipment and systems including EMS (Energy Management Systems) and SCADA (Supervisory Control And Data Acquisition). Furthermore they will also build on CLC/TC-57 in providing amendments to the ENs on (Communication networks and systems for power utility automation – EN-61850), along with Application integration at electric utilities (prEN-61968), energy management system application program interface (EMS-API) (prEN-61970) and on Power systems management and associated information exchange (EN-62351). The added value will also address the CEN-CENELEC-ETSI Coordination Group on Smart Energy Grids, CG-SEG (incl. the M/490 and its iteration) and EN-IEC-61850 (Distributed Energy Resources).

4. Concepts, architectures and use-cases of AI assisted smart PV

Solar energy has many important advantages, but also few important drawbacks. Among the advantages, it is a highly efficient energy source, which significantly advanced technologically in the recent years. It is a low cost and highly scalable, environmental friendly technology of energy generation. The main drawbacks of PV are cost/energy ratios (still improving and in 2020 historically becoming the cheapest energy source on Earth, however in highly solar irradiated geographic areas only), intermittence of power supply and not linearly fluctuating power output. Solutions for the areas of problems haunting PV are under significant development correspondingly with new materials and nano-engineering of the solar cells designs and fabrication methods, battery storage (or smart grid integration enabling input of PV generated surplus power to be consumed somewhere else) and electronic control equipment stabilizing electric output (smart hybrid converters and other devices). Furthermore facing the above problems many different optimization techniques were considered and implemented for PV modules and installations, mainly based on standard statistic techniques combined with numerical and analytical methods. Many of the these optimization techniques were also implemented by PV installations (or even PV modules) integrated electronic circuitry embedded in inverters, hybrid inverters, microinverters and alike. The better the optimization performance the higher the efficiency and power output stability of the optimized PV system which partially mitigates the main drawbacks of the PV technology, especially if it is interconnected to a smart power grid. Most of the PV optimization techniques considered were however classical and the recent development in Artificial Intelligence and Machine Learning can bring important added value in terms of better optimization of the PV modules and installations operations, hence further limiting the disadvantages of the electric solar energy.

The main areas in which AI can improve the PV performance are in solar cells designs and production phase, Planning of optimal solar cells systems deployments and optimization of solar cells operation in power systems. Solar cells designs and production phase comprises basic modeling of solar cells (materials, design and production technologies to devise new structures and designs, in terms of e.g. optimization of multi-junction cells, that haven't been considered yet but might surpass the efficiency of the current top solar cell designs). Planning of optimal solar cells systems deployments is about forecasting and modeling of meteorological data for weather dependent insolation patterns, shading, etc. – e.g. AI assisted automated insolation analytics and interactive maps for smart PV deployments, optimal sizing of photovoltaic systems based upon AI assisted modeling. Optimization of solar cells operation in power systems concerns AI assisted optimization of electricity generation in solar modules within grid-connected PV systems (machine learning upgraded electronic circuitry for improved MPPT, fluctuations stabilization, etc.), AI for PV performance loss rate determination and power forecasting on a level of single solar cells, solar modules as well as whole installations, from private residential PV setups, up to large scale PV power plants, advanced automation and optimization of Operation and Maintenance (O&M) of PV installations (both small and large scale) and their smart on-grid integration, including AI assisted PV powerplants predictive management (using AI and machine learning to learn patterns in the electric fluctuations to be able to predict failures and support operations in terms of prevention in right time rather than mitigating failures that have already occurred), AI enabled concentrator PV (CPV) learned productivity under variable solar conditions, AI assisted optimization of smart distributed PV integration with power grids towards interconnected and digitalized energy market - towards energy production with consumers changed into prosumers by local power generation enabling PV, complemented with AI to optimize all integration processes. The examples for the latter point (smart PV integration with smart grids) involve many possible applications of AI, such as e.g. AI for increasing the smart grid awareness, machine learning methods to improve on the statistical based power grids net-load forecasting with enhanced behind-the-meter PV visibility (including various models, e.g. based on recurrent neural networks for ahead in time net-load prediction under high intermittent solar penetration in power grids), AI for demand response potentials with high penetration of behind-the-meter solar with storage, AI assisted PV integrated smart grid connectivity tracking in real-time with various machine learning methods for state and events tracking, AI algorithms for managing PV penetrated smart grids in a way to optimize intermittence of solar power with power storage control, AI assisted carbon intensity awareness in the grid power production for the smart PV operation integrated with intelligent energy efficiency control, AI assisted integration of smart meters data to increase renewable energy penetration in different parts of the power grid (data mining and machine learning on vast amounts of bidirectional smart electricity meters data to improve over time operation parameters and physical restructuring of the power grid, towards a future of implementing automatically reconfigurable network topologies of electric power grids), AI assisted tokenization of virtual energy market (involvement of blockchain technology and smart contracts to securely tokenize prosumers generated surplus PV energy amounts, that physically enter the power grid but virtually enter a new generation of a distributed energy market with AI assisted algorithms for auctions of the energy selling/purchasing, so that the prosumers can gain on the transactions regarding their generated energy or possibly get it back from the grid for free in different locations and time), and others. Hence the approaches that can be used with applying AI to smart PV systems are vast and include among others: machine learning (with many variants including, supervised learning with classification and regression, as well as unsupervised learning with dimensionality reduction, clustering and association, deep learning and reinforced learning, quantum machine learning), neural networks (with many variants, including e.g. convolutional NNs, recurrent and feedforwarded NNs, generative adversarial NNs, quantum NNs), autonomous multi-agent systems (including particle swarm optimization), fuzzy logic (including quantum computational model based AI), expert systems (with knowledge bases and inference systems), evolutionary and genetic algorithms and other dynamically developed techniques and approaches. There is a wide consensus of advantages of new AI enabled methods over conventional statistical methods. An important aspect of the technical referencing of AI assisted smart PV (cf. Rządkowska, A., EITCI SESG AI assisted Smart PV Reference Standards, 2021) is not focusing on the theory of artificial intelligence and machine learning, but on practical AI applications in methods that are either ready to apply to PV operations or need only industrial level research and development.

5. Concepts, architectures and use-cases of AI assisted smart PV

Applying AI to important tasks for smart PV systems deployments and operations is undergoing significant investigation for several years already. The recent progress of AI may be very beneficial to support PV energy transition on a large scale. How exactly artificial intelligence can be successfully applied in different applications of photovoltaics? It should be noted that technical understanding of possible approaches is presently well developed however many particularities are under investigation in many currently ongoing R&D projects. Results of these projects will support further standardization of AI assisted smart PV.

5.1. AI assisted modeling of solar cell devices

This area of AI applications in PV has been discussed e.g. by Xu, 2019 or Miyake and Saeki, 2021.

In general a physical model governed by mathematical formulation accurately describing a solar cell design is a critical tool in for better understanding and fine-tuning of the characteristics, performance and optimization of a solar cell device. AI methods can in general assist in design and fabrication of solar cells.

A good example of how AI and machine learning supported modeling can benefit optimization of solar cells designs and construction is in the plasmonic enhancement of solar cells (cf. Jacak et al., 2011-2020). This can be well explained on a new generation of perovskite solar cells. An ordinary perovskite solar cell utilizes a perovskite structured compound (i.e. material with the same crystal structure as the $CaTiO_3$ – calcium titanium oxide), most commonly a hybrid organic-inorganic lead or inorganic tin halide-based material. It represents an emerging class of thin-film photovoltaic cells. Perovskites are efficient at absorbing light and transporting charges which are the key material properties for producing electricity from the sunlight. In contrast to traditional p-n junction semiconductor solar cells (like Si cells), perovskite cells are soluble in many different types of solvents and remain semi-transparent after crystallization in very thin layers. As such, perovskite SCs may be easily ink-jet or screen printed in simple roll-to-roll processes or even sprayed onto large surfaces similarly like ordinary paints that when activated with chemically induced crystallization process create thin-film layers (with the thickness below 1 μm) also relatively easily further integrated in elastic perovskite solar cell device. Those properties make the perovskite cells significantly cheaper in fabrication and very well suited to mass-output market uptake and vast applications (such as so called energy smart buildings elevations coverings of variety of geometries, semitransparent windows, roofs coverings, outdoor furniture, vehicles or even clothing external surfaces that may produce enough power from the sunlight to e.g. charge a personal mobile device). The main problem of the perovskite solar cells are lower efficiencies in applications-required chemically stable solar cell device configurations that might be greatly improved with optimized metalization in form of nano-particles inclusions and plasmonic energy mediation effects (cf. Jacak, 2020). This concept was proven specifically in perovskites in the initial experimental trials with a surprisingly strong magnitude of the plasmonic efficiency enhancement observed for perovskite (well beyond magnitudes in traditional p-n junction solar cells) but is not yet understood in terms of physical mechanisms involved and not described in physical models, nor developed commercially. Here with the aid come advanced ML enabled methods for modeling towards optimization and fine-tuning of the possible to employ very strong plasmon photovoltaic enhancement in metalized perovskite solar cells. This requires development of a microscopic quantum mechanical model of the new channel of plasmon mediated enhancement of the PV effect in perovskites which was confirmed in the recent experiments, taking into account that perovskite SCs hold a strategic potential for the EU, which managed to secure in the recent years a very strong position in terms of global competition in this area. A strong increase of the perovskite SCs efficiencies (the experimental record is 40% relative increase due to metalization as achieved experimentally) is most probably due to the reduction of the exciton binding energy, but not of plasmon induced strengthening of photon absorption known from the p-n junction solar cells (like the metalized Si cells). On the technological side, nanoparticles would be embedded in the perovskite compounds close to the interface with the electron or hole absorber in the architecture of a hybrid chemical perovskite cell. Such cells operate in a different manner than conventional p-n junction cells, resulting in a different type of the plasmonic PV effect, which, however, is surprisingly strong. Application of adequate treatment in quantum models (e.g. the Fermi golden rule to the coupling of the dipole near-field-zone - lower distance than the wavelength - radiation of surface plasmons in nanoparticles to the band electrons in a nearby semiconductor) can lead to advancing designs with AI enabled parameter optimization in a technological fine-tuning towards the innovative product development. This requires processing huge amount of data to account for most proper adjusting of the identified contributing components of this effect, an optical one present in p-n junction cells and resolving itself mainly to a photon absorption growth, and an electrical one - the newly discovered in perovskite cells apparently beyond absorption in a common general microscopic model. Model parameters optimizing for complex system is certainly a domain in which AI and ML can excel in current stage of these methods and technology development.

In general theoretical models describing solar cell device operation (in terms of physics of semiconductor structures involved) are primary tools in optimization of PV products efficiencies. A solar cell as a physical system is generally a simple semiconductor layered structure device of a p-n junction diode, producing electricity current from absorption of photons in a photovoltaic effect. Dominating semiconductor material in PV technology is the silicon - Si, either monocrystalline or polycrystalline. Depending on the complexity of the structure of the single-layered solar cell device (or a number of active solar cell layers in case of so-called multi-junction solar cell devices) the efficiencies to convert sunlight energy into electricity are between several percent up to even 40 percent (in complicated and expensive devices). Creating a numerical model of a solar cell involves most importantly its interaction with the e-m field. The e-m field simulation and its interaction with a semiconductor device can be done in specialized numerical methods such as the Finite Element Method (FEM) within a modeling suite called COMSOL. The modeling of the semiconductor device on its own is done in different approaches using electronic modeling tools used in electronic industry. The most important modeling parameters involve diode saturation current, series resistance, ideality factor, shunt resistance and the photocurrent (PV generated electricity). Many numerical as well as analytical approaches has been developed to simulate mutual interdependence of the solar cell characterizing parameters. Although the I-V relationship (referred to as I-V curve) is highly non-linear for solar cells which caused problems for many algorithms. Furthermore computational complexity for more complex devices is also problematic for a standard numerical approach. The more advanced approach partially based on ML and AI have been recently investigated with optimizing and modeling of the PV devices with a high rate of success. The currently identified as most promising directions were in simulated annealing combined with artificial neural networks. E.g. Karatape et al. developed an AI solar cell design optimization model basing on the Sandia National Laboratory data for PV performance in a function of operating temperatures and solar irradiation. A simple analysis proves that the relationship between the I-V curves is nonlinear and cannot be easily expressed analytically, which makes a great problem space for AI neural network to be utilized. Their 2006 paper proposed neural network based approach for improving the accuracy of the electrical equivalent circuit of a photovoltaic module, and as the equivalent circuit parameters of a PV module mainly depend on solar irradiation and temperature, the dependence on environmental factors of the circuit parameters was investigated by using a set of current–voltage curves. In a proposed model certain data points are chosen from the corresponding I−V curves (the selection of points is done upon a most optimal simplified but still accurate on the required level representation of the curve by a minimal number of points). The artificial neural network model is trained with as many possible combination of operating parameters (irradiation and temperature operation - the neural network is trained with empirical I-V curves, and the equivalent circuit parameters are estimated by irradiation and temperature readouts only, without nonlinear equations solving that would be necessary in conventional methods). The operation of this one of the first solar cells AI models has been verified in an experiment with the achieved empirical data highly corresponding with the data attained from the NN model and what's by far surpassing the accuracy from conventional numerical approaches. The results of ANN training was the a possibility to model an abstract device in given parameters combination (irradiation in temperature) to generate in ML approach an I-V curve enabling for the data to be input to a diode solar cell model. Different approach is in generating I-V empirically and determining operating points using ML (based on operating parameters of an experimental solar cell, I-V tracer and a weather station for readouts of irradiation level and the temperature and comparing the readouts with data attained in a model to provide a learning enabling feedback. The parameters generated by the model, despite being subject to errors and impossibility to discriminate between the effects on the operation of a modeled solar cell device of temperature vs. irradiation, were still superior (about 3 times more precise) then the ones possibly obtained from conventional models (in terms of Townsend equations solutions). Yet another approach is with utilization of the simulated annealing, as proposed by El-Naggar et al. (comparable with the genetic algorithms and particle swarm optimization methods). The operation of simulated annealing is based on defining an objective function and its minimization then validated against the experimental data (the method resulted with a Root Mean Square Error RMSE of just 0.0017 for a single diode solar cell model, which is considered highly accurate). On the other hand Askarzadeh et al. has proven that the Harmony Search optimization process provides even better precision, with the AI optimization method aiming at imitating an improvisation in music to find a harmony. Accordingly with the proposal an objective function based on the single diode model was minimized with respect to a particular range and the Harmony Search method was able to extract the main solar cell device parameters with an error (RMSE) significantly smaller (below one-tenth) than obtained in the simulated annealing method.

5.2. AI assisted smart PV applications in weather forecasting and automated insolation analytics for interactive irradiation mapping for smart PV deployments

This scope of AI application for PV is well addressed by e.g. Choi et al. (2019). When the solar cells device is manufactured and integrated into a solar module its efficiency is well defined. Upon its deployment it can be influenced with electronic control (involving smart hybrid inverters or a single panel adequate microinverters involving e.g. methods of AI assisted MPPT). However before the operational AI optimization of a PV installation is possible, an important aspect for proper planning in deployment of PV is weather forecasting (which also has an important role for smart grids operations). Predicting weather is not an easy task due to the complexity of the system, but making some well-informed analysis enables with the use of advanced ML models of some reasonable short term ahead of time estimation. Furthermore quantifying average irradiation and temperature (as the main important, however also backed up by humidity, wind speeds influencing cloud coverage changing affecting irradiation, daily sunshine duration and sunlight incoming angles, etc.) conditions allows to estimate the parameters of the PV installation that would generated certain required power to cover the expected loads. Meteorological analysis and estimation of the key weather parameters is hence an important factor in deciding the power output of the PV installation, as these parameters have an overwhelming influence on the efficiency of solar cells operation. Dedicated instrumentation (pyranometer, pyrheliometer, two-axis solar trackers, etc. are used to directly measure global and direct solar radiation). In certain places this data is available from already performed measurements stored in accessible databases (e.g. a database of NREL). Usually however these parameters are rather difficult to be obtained for given sites because of the PV systems installation planned in areas were these parameters have not been measured (low availability of data) and the direct measurements impractical because of the high cost of the equipment. Hence AI is an important alternative which recently has been used in aiding of solar irradiation mapping (along with other PV important meteorological parameters). How AI methods can be used to support mapping solar irradiation? Among multiple national and international projects there is gathered huge publicly accessible geographic data on insolation. An important application of AI assisted PV is employing data engineering of databases of insolation to provide a scalable and fast solution for computational analysis of conditioning PV parameters insolation in any geographical area (with using machine learning and AI estimation techniques for the low-data regions). An industrial case is the Project Sunroof initiated by Google as a planned extension to Google Maps product, that would provide full analytics of insolation data from multiple sources joined and processed by Google algorithmics and merged with Google Maps. Project Sunroof was started by a Google engineer Carl Elkin. The initiative's purpose is mapping the planet's solar potential, one roof at a time. The Project Sunroof primarily works to encourage the private adoption of solar energy by providing a set of tools to facilitate the purchase and installation of solar panels. Using data from Google Maps to calculate shadows from nearby structures and trees and taking into account historical weather and temperature patterns data, the Project Sunroof calculates how much money a user can expect to save yearly by making use of the solar power PV installation. In addition, the Project Sunroof also provides a list of local solar power retailers capable of installing solar panels in that area. The Project Sunroof was initially launching only in the United States, for the cities of Boston, San Francisco, and Fresno. The project has then expanded to cover larger metropolitan areas across the United States and is currently developing globally. The Google's Project Sunroof bases on the data of imagery and 3D modeling and shade calculations from Google, weather data from the National Renewable Energy Laboratory (NREL), utility electricity rates information from Clean Power Research, solar pricing data from NREL's Open PV Project, California Solar Initiative, and NY-Sun Open NY PV data, solar incentives data from relevant policy actors, Solar Renewable Energy Credit (SREC) data from Bloomberg New Energy Finance, SRECTrade, and relevant state authorities, aggregated and anonymized solar cost data from Aurora Solar software. A similar but less visual solution – PVWatts tool – was developed by the National Renewable Energy Laboratory (NREL). Similarly as Project Sunroof It estimates solar energy production in taking into account multiple factors, e.g. sun shading by objects, typical weather patterns, equipment parameters, etc. The estimations are based on multiple databases, in many cases with many historic data for proper predictions e.g. of averaged weather conditions for insolation, as well as complicated analyses for shading (algorithms take into account even recent growth or removal of trees to most accurately analyze solar power potential, hence proper datamining in AI/ML techniques is important enabler of this technology for its future development). Project Sunroof's expanded its reach to Europe partnering with E.ON and released a new online tool in Germany based on Google's Earth mapping to help residential customers determine whether their roof is well-suited for solar panels and how much money they could save by installing solar. The main focus of this area of AI assisted smart PV is to help raising consumer solar awareness, and on making the path to solar easier for its customers and operations. Project Sunroof's estimates in Europe include weather data from Meteonorm, a product by Meteotest, a Swiss company specializing in solar irradiance data. AI enabled extensions involve recent cooperation between Google and Total (French energy company with a large network of gas stations in Europe and in Africa). Total developed the Solar Mapper tool using AI enhanced Google solution to make solar potential estimation faster and easier, driving the adoption of solar power globally by using machine learning to model estimates in low-data areas. For an example of France the project increased the territory covered for solar estimation from 30% to 90% using AI, which in turns encourages solar power uptake. Estimating potential output of solar panels on private houses, or on commercial and industrial sites is an important incentive in encouraging the PV uptake worldwide. The actual AI algorithms used generative predictive models to enhance the 3D data used to model shade and calculate solar potential where high-quality satellite images are not available. By doing this, AI helps to estimate the solar output for positioning solar panels on any location. Principal investigator in the project is Philippe Cordier (and the team involves Google Earth Engine and Google Cloud machine learning experts). Also widespread adoption of rooftop photovoltaic systems in residential PV installations, as well as growing grid-scale solar systems requires a significant change in how system operators, utilities and solar system providers map system adoption, track it is impact, and plan new deployments. Currently available information suffers from disparities in resolutions (satellite imaging is usually detailed in dense populated areas but much less so in rural areas, also significantly differentiated in terms of countries). It also often lacks crucial details about time and location. The availability of such information would change how the system is planned and managed. Artificial intelligence and machine learning techniques may prove to be crucial to effectively map of the optimal deployment of PV systems by supporting lower intensity data with estimation, thus supporting highly aware and hence optimized distribution networks with high accuracy and detail. The AI assisted in generation and continuously updated global database joining public accessible data from project such as NREL insolation database or Google's Sunroof Project may be a future of aware planning of small-to-large scale solar energy deployments. Recent advances in AI in effective processing huge datasets enabling to combine information available at a large scale (such as satellite imagery, Google street view images processed with AI vision for unlocking machine-understanding of shading and high-resolution irradiance data from weather stations and historical measures of solar irradiation parameters, hold a potential to generate a vastly optimized plans for location and size of future solar deployments globally thus supporting certain reconfigurations and reconstructions of the transmission lines or distribution grids as necessary for future deployments. This area of application holds potential especially if combined with high spatiotemporal granularity, which requires adjusting of most proper methods in machine learning approaches to process all the extremely detailed data and address a variety of applications such as identifying bottlenecks, estimating the hosting capacity of distribution systems, planning electric storage capacity in dependence to conditioning circumstances of locations, improving wholesale price predictions, and creating more accurate models of consumer adoption.

5.3. AI assisted carbon intensity awareness in the grid power production for smart PV operation

This field of AI application for smart PV has been discussed by Khana (2018) and Tuzun (2020). Prosumer centric, distributed energy model enabled by smart PV in standard integration with the smart grid, enables PV power generated surplus to be fed into the grid. The bidirectional smart meter measures the power input to the grid and enables intake for consumption when the electric energy is needed beyond the current capacity of the PV generation. In this model however the smart PV and energy consuming appliances integrated installation does not know when it is most optimal to actually use the energy generated In surplus that would be fed to the grid. This requires awareness not only on electric net loads in the grid but also awareness of when the grid power has the smallest CO_2 footprint. The resolution of the carbon intensity forecast is required to be at least on a regional level for the technology to allow prosumer installations to actually condition their energy consumption on this environmental factor. For the technology to work AI and Machine Learning is a key enabler, because of a sophisticated power system modelling required to accurately to forecast the carbon intensity and generation mix up to 4 days ahead for individual regions. Such achievement had been already introduced in Great Britain in terms of the Carbon Intensity API project (of the UK National Grid ESO). The outcomes of the project are successful to the extent that the UK National Grid has produced and delivered thousands of WiFi connected bulbs that change the emitted light color to green whenever the electricity in the grid is dominantly from low-carbon sources (thus giving a signal that it is a good and environmentally clean time to do a laundry in a washing machine, to turn on a dish washer or to start charging an electric car – in smart home integrated IoT, all this would be automatic along with properly managing surplus of power generated by AI assisted and interconnected PV installation accordingly with the awareness of the current regarding the carbon intensity of grid power). The open API of the project enables prosumers and smart devices to schedule energy consumption in coupling with smart PV local power generation in order to minimize CO emissions at a regional level. The data in the API estimate and indicative trend of regional carbon intensity of the electricity system in 96 hours ahead of real-time, thus providing programmatic and timely access to both forecast and estimated carbon intensity data (limited to electricity generation only). The CO_2 emissions (within a measure of how much of CO_2 is produced per kilowatt hour of electricity consumed) are gathered from all large metered power stations, interconnector imports, transmission and distribution losses, and account for national electricity demand, embedded wind and solar generation. The API allow developers to produce applications that enable consumers or smart devices to optimize their behavior in such a way as to minimize CO_2 emissions. While the actual value is the estimated carbon intensity from metered generation, the more ambitions target is the time-ahead forecast value. Since the carbon intensity of electricity is sensitive to small changes in carbon-intensive generation. Carbon intensity varies by hour, day, and season due to changes in electricity demand, low carbon generation (wind, solar, hydro, nuclear, biomass) and conventional generation. National Grid ESO forecasts the carbon intensity and generation mix of electricity consumed across 14 geographical regions in Great Britain. The spatial and temporal characteristics of carbon intensity can be visualized on maps or be transferred in computational datasets. How the AI and Machine Learning techniques are actually involved in this application? The demand and generation by fuel type (gas, coal, wind, nuclear, solar etc.) for each region is forecast several days ahead at 30-min temporal resolution using an ensemble of state-of-the-art supervised Machine Learning (ML) regression models. An advanced model ensembling technique is used to blend the ML models to generate a new optimized meta-model. The forecasts are updated every 30 mins using a nowcasting technique to adjust the forecasts a short period ahead. To estimate the carbon intensity of electricity consumed in each region, a reduced GB network model is used to calculate the power flows across the network. This considers the active and reactive power flows, system losses, and the impedance characteristics of the network. The carbon intensity of both active power flows (gCO /kWh) and reactive power flows (gCO /kVArh) is then calculated and the CO flows are attributed around the network for each 30 min period over the next several days. The carbon intensity of the power consumed in each region is then determined. The same approach is used to estimate the proportion of each fuel type consumed in each region. A more detailed description of the Carbon Intensity API methodology can be found in reports by Rogers, A., Bruce, A., et al., 2021.

5.4. AI assisted integration of smart meters data to increase renewable energy penetration

One of the important applications of AI for smart PV is the use of machine learning techniques to process (including joining, synchronizing, standardizing and interpolating) electric data from numerous sources (especially smart meters) in order to more accurately estimate the state of the electric grid. This will ultimately support efficiency for interconnection and/or operation of more PV systems and other Distributed Energy Resources (DER) in power grid while simultaneously enhancing reliability, stability and resiliency of power provision. This area of AI application involves measurements and sensor data synchronization, data mining for error detection and identification, data based reasoning and machine learning based optimization. Vast amounts of the smart meters data provided by the Advanced Metering Infrastructure (AMI) and Phasor Measurement Units (PMU) is a great target for AI assisted processing, reasoning and optimization methods that will lead to significant increase of smart PV installations grid-integration efficiency and scale. The scope discussed has been addressed by e.g. Boza et al. (2021), as well as Bañales et al. (2021).

5.5. AI assisted PV powerplants predictive Operation and Maintenance (O&M) optimization

AI and ML methods are well suited optimize O&M of photovoltaic (PV) power plants by detecting, classifying and monitoring anomalies and malfunctions along with the prediction and mitigation. The AI systems can predict failures and prevent their occurrence based on vast data processing abilities with well-informed reasoning on the reasons and circumstances preceding possible malfunctions. Such predictive AI O&M solutions is of critical importance for industry-level PV power plants with large number of solar cells modules and complex interconnection systems, as due to the machine learning capabilities the system would increasingly better predict failures and allow to schedule proper maintenance. Predictive O&M is an important aspect of the smart O&M to sustain a high profile and economically optimized performance of a solar PV plant and reduce its downtime. Real-time monitoring data of various system outputs, such as the as power output, other more detailed probing of the electricity signature, detection of fluctuation patterns, temperature sensors readouts, combined with accurate weather information sensor networks can be meaningfully processed by AI algorithms in neural networks models trained and self-improving in identification of the common fault class patterns. The most adequate systems are various models of neural networks as well as hierarchical generative models and as proposed in recent projects – probabilistic information fusion framework fed with data from both the sensor level and the system level. More details can be found e.g. in a paper by Chang et al. (2019).

5.6. AI for increasing the smart grid awareness

This area of AI application were discussed e.g. by Omitaomu and Niu (2021), as well as by Jiao (2020). AI and ML can be used to provide grid operators smart monitoring and decisions support in real-time analysis and visualization of the electric power system operations. AI assisted cloud computing enables advanced monitoring, while real-time analytics provide a model for leveraging multiple data sources to correlate, verify, and interpret system telemetry in environments with high scale and low data fidelity. Machine learning is especially well applied in such areas as fluctuations in data can be detected with increasing accuracy of prediction with increasing history of operations and available data. Experience from systems design in related fields shows that in sufficiently complex systems, no single data source can be entirely accurate or trustworthy, but an approach that leverages multiple sources and applies intelligent data interpretation can provide an extremely reliable, high-fidelity systems view. This area of application of AI for smart monitoring along with capabilities in integrated power system simulation and data analytics with machine learning or deep learning enables provision of advanced, integrated situational awareness for the distribution grid and contributions to area-wide flexibility.

5.7. AI for PV performance loss rate determination and power forecasting

This area of applying AI is by using spatiotemporal Graph Neural Network models in a so-called Reliable System-Topology-Aware Learning Framework. More details in this regard has been presented by the US Department of Energy Project: Robust PV Performance Loss Rate Prediction: Using Spatiotemporal Graph Neural Network Models in a Reliable System-Topology-Aware Learning Framework (DE-EE0009353, 2021).

A similar discussion can be also found in a paper by Zhou et al. (2021). The AI and ML techniques are used to analyze data from a large number of neighboring PV systems in order to extract high amounts of information about their short- and long-term performance. Machine learning methods are planned to be used to overcome data quality issues affecting individual plants. Development of spatiotemporal Graph Neural Network models addresses critical questions of long- and short-term performance for fleets of PV plants for their operators and also for the grid status determination. The proposed learning techniques advance both analytical techniques for long-term performance of PV power plants and deep learning techniques, and can mitigate the negative impact of PV plant or sensor failure or unreliable input data.

5.8. Deep Learning probabilistic net load forecasting with enhanced behind-the-meter PV visibility

Another area of AI application for PV (as introduced by Kirschen et al. in 2018 and developed further by Cha and Joo in 2021) is using machine learning and deep learning techniques to predict the electric load one day in advance in areas that have large amounts of behind-the-meter solar. The AI predicted information on the future net load will allow operators (or AI supported control systems) to manage the electric grid more efficiently (in terms of compensating loads and costs). The deep learning based probabilistic forecasting framework for a day ahead net load at substations aims at separation of the behind-the-meter photovoltaic generation from net load measurements and quantifies its impact on net load patterns. Actual AI DL applications requires implementation of the transfer learning models that would enable transferring the knowledge learned from geographic locations with rich sensor data to diverse locations where only the substation measurements are available. The framework could be validated using measurement data from public grid databases as well as basing on the Solar Forecast Arbiter platform.

5.9. AI for demand response potentials with behind-the-meter solar with storage high penetration

This aspect of AI application assisting smart PV (discussed in detail by Wattam et al. in 2020, as well as by Esnaola-Gonzalez et al., and Prabadevi et al. in 2021) is based on machine learning techniques to predict the electric load in areas with large amounts of solar energy to enable more efficient grid operation. ML application will also be able to forecast the capacity available to the grid from electric loads that can be turned on or off depending on the balance between electric demand and generation. Recent advances in AI modelling can enhance the accuracy of net load forecasting, the observability of net load variability, and the understanding of the coupling between net load and demand response potentials. There are two models under development for addressing hybrid probabilistic forecasting which can provide better spatiotemporal information.

5.10. AI assisted PV integrated smart grid connectivity tracking in real-time with heterogeneous data sources by application of graph learning assisted state and event tracking

Another scope of AI application in smart grid integrated PV is for its connectivity tracking in real-time with heterogeneous data sources by application of graph learning assisted state and event tracking. This area has been recently researched by i.a. Albayati et al. (2021), Koshy et al. (2021), as well as Esenogho et al. (2022). Machine learning techniques enable integration of large-scale electric data and use it to calculate the overall state of the electric network. This scope partially expands on the Operations & Maintenance (O&M) AI smartPV application but addresses it from a specific perspective of graph based learning which might be especially adequate to a grid graph-like topology. The resulting AI enabled tool will detect connectivity changes and faults in the grid and update the grid models accordingly, which will improve the situational awareness of power grids with large amounts of solar energy by exploiting a large volume of data and measurements available from a highly diverse set of sources (especially in terms of measured characteristics of the electricity in the grid). This scope of AI application for smart PV also considers tools to detect, identify and track network topology changes, that might be due to unexpected disturbances or switching events by exploiting the recently developed sparse estimation methods in the data analytics area.

5.11. Variational recurrent neural network based net-load prediction under high solar penetration

A different in applications is using artificial intelligence and machine learning techniques to create tools that can predict future electric loads (e.g. in scale of hours or days) in areas with large amounts of behind-the-meter PV systems and deliver savings in the operation of the electric network. There are proposed concepts (e.g. Liu et al., 2019) in development and validating of variational recurrent model-based algorithm for time-series forecasting of net-load under high solar penetration scenarios. In uncertainty of cloud covering weather conditions, varying solar irradiance, geographical information with details including shading, and the measured end-use load may theoretically guarantee tight bounds on the net-load prediction, that can be obtained from vast datamining and properly trained machine learning models working on that data jointly.

5.12. AI enabled concentrator PV (CPV) learned productivity under variable solar conditions

Beyond standard PV installations, artificial intelligence and machine learning techniques can be used also to model and optimize concentrator PV plants operations in order to assist human operators in their decisions, especially during variable cloudiness conditions. The machine learning techniques can be applied to extensive, high-resolution, inferred DNI data, cloud profile and vector data, and related solar field thermal collection data in order to develop prescriptive models to optimize solar field collection under variable conditions while minimizing long-term PV receiver damages and other negative effects. Validation of methods that can be used to this end for CPV are currently underway in regard to operating concentrating solar power (thermal) CSP facilities and start to publish methodological details for broader investigations. Even though that there are certain differences in concentrating solar power for thermal and PV applications (the former being usually central while, the latter much more distributed into multiple lower-power PV receivers), certain disadvantages of the CSP vs CPV (including environmental issues), seem to favor the latter at least in a long term of the technology development, and AI assistive role in optimization of CPV operations is certainly an important aspect. More details in this regard can be found in papers by Renno et al. (2020) and Tina et al. (2021).

AI advances to improve and further optimize the performance and reliability of individual solar cells, solar modules and PV small-to-large scale installations (from residential to utility power plants), along with AI enabled predictions of solar energy output and electric-network situational awareness (also including the awareness of how clean the energy in the grid is in the current moment along with ML prediction for ahead of time, to enable smarted AI assisted energy consumption management for reducing emissions) play an important role in supporting large scale PV energy transition. The current cooperation which is beginning to scale internationally between AI experts and solar energy industry stakeholders will be further stimulated by the relevant technical standardization efforts, with a goal to advance AI smart assisted PV technology. The standardization activity in the scope of AI assisted smart PV will facilitate its faster market uptake and speed up the clean energy transition globally.

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