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Reference Standard

RS-EITCI-SESG-SMART-PV-TECHNICAL-STD-VER-5.0

Reference Standard for the Smart AI Assisted Photovoltaic Systems
Technical Specification of Processes and Devices

EITCI INSTITUTE SMART ENERGY STANDARDS GROUP

EITCI-SMART-PV-SESG

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1. Introduction

Global energy demand is increasing in a high pace, while greenhouse gases emission peak. International agreements (such as the Paris Agreement) aim and saving the day with speeding-up plans for reaching zero-net emissions and phasing out fossil fuels wherever it is possible.

With technological progress renewable energy with particular potential on the side of PV with increasing efficiencies to costs ratios emerge as realistic alternatives. Large scale adoption is started to be driven by policy and market initiatives as well as by increasing social awareness of the necessity to transit to the clean energy. The main practical challenge in deployment of PV on a massive scale is in its intermittence. The smart grid and battery systems are developing rapidly and provide increasingly efficient solutions to this challenge. One of the particularly promising technology, a key enabled of efficient interplay of PV systems and its grid integration is artificial intelligence and machine learning.

Applying AI technology aims at enabling significant advancement in photovoltaics and solar energy generation due to machine learning enabled data science based optimization of vast historic and real-time datasets of operational parameters and external circumstances (these can be gathered by sensors, sensor networks, and energy operators). AI assisted PV holds a disrupting potential for the solar energy industry.

All indicated AI assisted smart PV technology development directions are consistent with the goals set out by the EU and make a field of high interest for relevant stakeholders to enter international partnerships and initiate standardizing activities.

Key-words: Smart PV, AI, Photovoltaics, Smart grids, Smart metering, Smart energy, MPPT

2. Technical specification of processes and devices

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.

3. Introduction to Artificial Intelligence (AI)

AI is a discipline of computer science concerned with designing computational systems able to introduce machine understanding and data processing intelligence. The goal of AI is to solve problems in a similar way to humans do, hence artificial intelligence. Due to recent machine learning advances AI technologies are either replacing conventional techniques or are being integrated into existing systems to support their operation in an intelligent manner. Mostly applications of AI relate to optimization of operation of complex systems.

Certainly artificial intelligence is area that contain many different approaches. Some have recently proven better then others (sometimes inversing the trends from the past, which makes a realistic the expectation that the trends will shift again, meaning that no approach should be left over and all should be investigate in technical terms to facilitate smart PV). Recent progress in AI has been dominated by machine learning (ML), coming in many variants (including data-hungry deep learning, human learning indicated reinforcement learning techniques and many others). In general in ML (implemented most usually on artificial neural networks, i.e. interconnected graphs of information processing nodes, which to some extent aim at modeling a brain) computational systems try to implement an ability to learn on a basis of observation of processes dynamics (usually associated with so called data-analytics / engineering from vast sets of data, using real life operative parameters of different complex processes, which are attained in so-called data mining), rather then being directly programmed to undertake certain steps (as it is in conventional imperative or functional algorithmics).

Using multiple various statistical techniques such machine learning algorithms are capable of finding best solutions (or improving existing) regarding many practical problems only by computationally-fast (far superior to human possibilities) processing of huge data sets to support or fully automate decision making in high quality prediction and estimation of different factors. It is a matter of discussion whether AI is (or will be) really generally superior to humans, but it is a well known truth that in certain tasks the way of machine computation is beyond possibilities of humans (like for example instant performing of huge calculations).

It is also evident that humans are still far superior to AI in visual patterns recognition or in natural speech, which however might be a subject of change. It is expected though that applying AI to certain tasks (most usually associated with data-intensive tasks, well suited to complex systems parameters monitoring and management with possible prediction of missing data or the data that will be attained in the future based on the past data patterns) is a proper direction which brings a lot of added value (the best example is how machine learning assisted techniques revolutionized knowledge distribution in the society driving evolution of Internet with increasingly intelligent search engines).

3.1. Machine Learning (ML)

Machine learning (ML) is the study of computer algorithms that improve automatically through experience. It is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.

Conditioned by different approaches to learning, ML algorithms can be hence classified in many ways. In a most general classical the ML methods can be divided into supervised learning, unsupervised learning and reinforcement learning.

Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks. Machine learning was defined in 1959 by Arthur Samuel as the "field of study that gives computers the ability to learn without being explicitly programmed".

A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers, however not all machine learning is statistical learning. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics.

As mentioned, machine learning approaches are traditionally divided into three broad categories, depending on the nature of the "signal" or "feedback" available to the learning system:

Supervised learning: The computer is presented with example inputs and their desired outputs, given by a teacher, and the goal is to learn a general rule that maps inputs to outputs.

Unsupervised learning: No labels are given to the learning algorithm, leaving it on its own to find structure in its input. Unsupervised learning can be a goal in itself (discovering hidden patterns in data) or a means towards an end (feature learning).

Reinforcement learning: A computer program interacts with a dynamic environment in which it must perform a certain goal (such as driving a vehicle or playing a game against an opponent). As it navigates its problem space, the program is provided feedback that's analogous to rewards, which it tries to maximize.

3.1.1. Supervised learning

In supervised learning, a supervisor or a teacher must support the algorithm in learning its parameters. These algorithms require a data set that contains information about both the input data and the output. During the learning phase, when the algorithms try to make predictions about the data set, the teacher corrects and guides the algorithms in the right direction so that they improve over time. Additionally, supervised learning methods can be broken down into two main categories depending on the output variable they want to predict. If the output data is a discrete variable, e.g. For example, to determine whether the next day is sunny, cloudy, or rainy (class 1, 2, or 3), these cases are referred to as a classification problem.

On the other hand, when the required power is a continuous or real value, e.g. For example, trying to predict the irradiance of a city over a certain period of time, or trying to determine the best size of a PV module, turns the case into a regression problem. Some examples of supervised learning algorithms include linear and logistic regression, k-Nearest Neighbors, neural networks, and more robust algorithms such as deep neural networks and their variations. Figure 1 summarizes the concept of an artificial neural network inspired by biological networks in the brain. An ANN therefore contains three layers (input, hidden and output), connections, distortions, weights, an activation function and a summation node. These weights and biases are important parameters that affect the output function.

3.1.2. Unsupervised learning

In contrast, unsupervised learning algorithms do not require a supervisor to learn the input data or make predictions. In this case, these types of algorithms only require one set of input data. Your goal is to correctly learn a model that best represents the given data. As these algorithms rely on finding patterns in the input data, unsupervised learning methods are therefore mainly used consist of clustering algorithms like K-means and self-organizing cards.

3.1.3. Reinforcement learning

In reinforcement learning, in contrast to the previous two areas, the algorithms for reinforcement learning are based on a goal-seeking approach in which the learner tries different actions to find out which are best suited to achieve a particular goal. Some examples of reinforcement learning algorithms include Q-learning and Monte Carlo methods.

3.1.4. Other AI ML methods

Other possible and investigated ML approaches include autonomous multi-agent systems (including particle swarm optimization), fuzzy logic (including quantum computational model-based AI), expert systems (with knowledge based and inference systems), evolutionary and genetic algorithms, and other (e.g. simulated annealing or ant colony methods). Such techniques do not imperatively solve specific tasks within a range of constraints as it is most usually intended in conventional programs, but rather try to operate independently from imperative step-by-step approach using different approaches of sometimes chaotic attainging of solutions. E.g. expert systems have been developed to solve problems within the same high-level abstraction approach as humans (using the acquired knowledge and a logical inference systems to make statements, predictions and decisions). An expert system usually consists of two main components: an inferential logic system and a knowledge base. The knowledge base contains facts and rules, while the inference engine aims to apply these rules and facts to infer about new knowledge (the validating and if actually verified, also populating the knowledge database, becoming a basis for further predictions).

A number of optimization techniques as inspired by nature have been developed as well in the field of AI methods. These include genetic algorithms first developed by Holland (1975) based on the principles of genetics and evolution (with slightly modified or mutated self-copies of the algorithms populating evolution space). On the other hand, the ant colony approach is another computer optimization model that was inspired by the behavior of ants able to find the shortest routes as formulated by Dorigo (1992). In this nature-inspired approach ants move at random to look for the optimal route to their food, but while moving they leave their pheromones, hence the stronger the pheromones the more likely ants will follow that particular path at strengthen it even more so. This method is successfully applied to optimize machine planning and telecommunications networks and might find its application towards smart power grids dynamic restructuring in the future. Other inspired by nature approaches include particle swarm optimization (influenced by a flock of birds).

A different optimization technique involves fuzzy logic (proposed by Zadeh, 1965), which has become a branch of computer logic that differs from conventional (Boolean) logic, in that regard that binary values of 1 corresponding to true and 0 corresponding to false logic values, are rather replaced a spectrum mixing these two discrete values (usually in a probabilisty way, but in case of quantum mechanics in a completely non-classical and non-local way giving rise to the phenomenon known as a quantum superposition or a qubit, a quantum analogue of a two-dimensional logic systems known classically as bit). Fuzzy logic is often used in combination with expert systems and with neural networks. It strongly influenced development of quantum artificial intelligence, when superpositions of states and interconnections between nodes of quantum neural networks can benefit of exponentially scaling state systems quantum parallelism. Other physical sciences bases approaches involve simulated annealing as an effective optimization technique (proposed by Kirkpatrick et al). It has been inspired by the process of heating and slowly cooling solids and can be used to maximize or minimize a function. Recent progress in quantum annealing have advanced this method through the use of the quantum mechanical process of tunneling electrons through a barrier of energy potential (so called Josephson junctions), making non-universal quantum computer models excellent for optimizing complex problems that can be reduced to finding local minima of an oscillating function. This latter approach could prove to be particularly useful for investigating and optimizing the intelligent power grid input control of a very unstable PV-generated power in a real-time signal processing (therefore necessarily fast).

Also other approaches have been developed which are already were or are undergoing investigations for practical AI applications.

Many of these discussed above and other as well, do not fit well into the three-fold categorisation of the machine learning as discussed in the previous chapters. Sometimes it is beneficial to use more than one method in the same machine learning system for beneficial results. This involves for example topic modeling combined with dimensionality reduction or meta learning.

It should be however stressed that as of 2020, the so called deep learning approach (based on querying huge datasets) has become the dominant approach for much ongoing work in the field of machine learning.

3.1.5. Deep learning

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. As discussed machine learning can be supervised (also semi-supervised) or unsupervised. Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, machine vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance. Artificial neural networks (ANNs) were inspired by information processing and distributed communication nodes in biological systems. The adjective deep in deep learning refers to the use of multiple layers in the network. Early work showed that a linear perceptron cannot be a universal classifier, and then that a network with a nonpolynomial activation function with one hidden layer of unbounded width can on the other hand so be. Deep learning is a modern variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability, hence the structured part.

4. Practical AI solutions that may be utilized and integrated into AI assisted smart PV

One of the important AI models implementation platforms is Google Cloud. Google Cloud in its core mission is highly focused on delivering high abstract level AI services and performing as high-end machine learning platform. Some of the Google Cloud AI services include:

- Cloud AutoML – Service to train and deploy custom machine, learning models.
- Cloud TPU – Accelerators used by Google to train machine learning models.
- Cloud Machine Learning Engine – Managed service for training and building machine learning models based on mainstream frameworks.
- Cloud Vision API – Image analysis service based on machine learning
- Cloud Video Intelligence – Video analysis service based on machine learning

Google AI is a special division of Google dedicated to artificial intelligence. The mains projects of Google AI include:

- Serving cloud-based TPUs (tensor processing units) in order to develop machine learning software, as well as development a dedicated high-level abstraction software library for AI modeling in different languages, the TensorFlow.
- The TensorFlow Research Cloud gives researchers and engineers free cluster of one thousand cloud TPUs to perform machine learning research on, under the condition that the research is open source and they put their findings and publish it in a peer-reviewed scientific journal. Portal to thousands of research publications by Google staff.
- Sycamore: a 54-Qubit Programmable Quantum Processor.
- Google Brain, which is a large scale a deep learning artificial intelligence research project at Google, formed in the early 2010s, combining open-ended machine learning research with information systems and large-scale computing resources. The Google Brain project began in 2011 as a part-time research collaboration between Google Fellow Jeff Dean, Google Researcher Greg Corrado, and Stanford University professor Andrew Ng. Ng had been interested in using deep learning techniques to crack the problem of artificial intelligence since 2006, and in 2011 began collaborating with Dean and Corrado to build a large-scale deep learning software system, DistBelief, on top of Google's cloud computing infrastructure.

Google Brain started as a Google X project and became so successful that it was graduated back to Google: Astro Teller has said that Google Brain paid for the entire cost of Google X. In June 2012, the New York Times reported that a cluster of 16,000 processors in 1,000 computers dedicated to mimicking some aspects of human brain activity had successfully trained itself to recognize a cat based on 10 million digital images taken from YouTube videos. Since the early years of the project, Google Brain has significantly advanced and finds many applications in Google AI products.

4.1. Python for AI modeling

Python is an interpreted, high-level and general-purpose programming language. Python's design philosophy emphasizes code readability with its notable use of significant whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. Python is often described as a "batteries included" language due to its comprehensive standard library. Python is commonly used in artificial intelligence projects and machine learning projects with the help of libraries like TensorFlow, Keras, Pytorch and Scikit-learn. It is a dynamically-typed (executing at runtime many common programming behaviours that static programming languages perform during compilation) and garbage-collected (with automatic memory management). It supports multiple programming paradigms, including structured (particularly, procedural), object-oriented and functional programming. Python interpreters are supported for mainstream operating systems and available for a few more (and in the past supported many more). A global community of programmers develops and maintains CPython, a free and open-source reference implementation. A non-profit organization, the Python Software Foundation, manages and directs resources for Python and CPython development. As of January 2021, Python ranks third in TIOBE's index of most popular programming languages, behind C and Java, having previously gained second place and their award for the most popularity gain for 2020. It was selected Programming Language of the Year in 2007, 2010, and 2018. An empirical study found that scripting languages, such as Python, are more productive than conventional languages, such as C and Java, for programming problems involving string manipulation and search in a dictionary, and determined that memory consumption was often "better than Java and not much worse than C or C++". Python, as a scripting language with modular architecture, simple syntax and rich text processing tools, is most often used for programming practical artificial intelligence applications.

4.2. TensorFlow

TensorFlow is a free and open-source software library for machine learning (that is most widely used in combination with Python). It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks. It is a symbolic math library based on dataflow and differentiable programming. It is used for both research and production at Google.

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache License 2.0 in 2015. Starting in 2011, Google Brain built DistBelief as a proprietary machine learning system based on deep learning neural networks. Its use grew rapidly across diverse Alphabet companies in both research and commercial applications. Google assigned multiple computer scientists, including Jeff Dean, to simplify and refactor the codebase of DistBelief into a faster, more robust application-grade library, which became TensorFlow. In 2009, the team, led by Geoffrey Hinton, had implemented generalized backpropagation and other improvements which allowed generation of neural networks with substantially higher accuracy, for instance a 25% reduction in errors in speech recognition.

TensorFlow is Google Brain's second-generation system. Version 1.0.0 was released on February 11, 2017. While the reference implementation runs on single devices, TensorFlow can run on multiple CPUs and GPUs (with optional CUDA and SYCL extensions for general-purpose computing on graphics processing units). TensorFlow is available on 64-bit Linux, macOS, Windows, and mobile computing platforms including Android and iOS. Its flexible architecture allows for the easy deployment of computation across a variety of platforms (CPUs, GPUs, TPUs), and from desktops to clusters of servers to mobile and edge devices.

TensorFlow computations are expressed as stateful dataflow graphs. The name TensorFlow derives from the operations that such neural networks perform on multidimensional data arrays, which are referred to as tensors. During the Google I/O Conference in June 2016, Jeff Dean stated that 1,500 repositories on GitHub mentioned TensorFlow, of which only 5 were from Google. In December 2017, developers from Google, Cisco, RedHat, CoreOS, and CaiCloud introduced Kubeflow at a conference. Kubeflow allows operation and deployment of TensorFlow on Kubernetes, thus easily integrated practically unlimited capacity of the cloud AI with practical neural networks model for advanced machine learning tasks, that could well integrated with AI assisted smart PV.

4.3. Keras

Keras is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library. Up until version 2.3 Keras supported multiple backends, including TensorFlow, Microsoft Cognitive Toolkit, Theano, and PlaidML. As of version 2.4, only TensorFlow is supported. Designed to enable fast experimentation with deep neural networks, it focuses on being user-friendly, modular, and extensible. It was developed as part of the research effort of project ONEIROS (Open-ended Neuro-Electronic Intelligent Robot Operating System), and its primary author and maintainer is François Chollet, a Google engineer. Chollet also is the author of the XCeption deep neural network model.

Keras contains numerous implementations of commonly used neural-network building blocks such as layers, objectives, activation functions, optimizers, and a host of tools to make working with image and text data easier to simplify the coding necessary for writing deep neural network code. The code is hosted on GitHub, and community support forums include the GitHub issues page, and a Slack channel. In addition to standard neural networks, Keras has support for convolutional and recurrent neural networks. It supports other common utility layers like dropout, batch normalization, and pooling.

Keras allows users to productize deep models on smartphones (iOS and Android), on the web, or on the Java Virtual Machine. It also allows use of distributed training of deep-learning models on clusters of Graphics processing units (GPU) and tensor processing units (TPU). Keras has been adopted for use in scientific research due to Python (programming language) and its own ease of use and installation. Keras was the 10th most cited tool in the KDnuggets 2018 software poll and registered a 22% usage.

5. Applications of AI to smart PV - processes and devices

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

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.

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. 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 $CaTiO3$ – calcium titanium oxide, originally discovered in 1839 and named after Russian mineralogist Lev Perovski), 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 same properties make these cells specially interesting for advanced space applications in replacing of the sturdy and heavy panels with in-orbit printed (from the liquid solvents containers) flexible and large-surface sheets of thin-film solar modules or coverings for objects in space, even facilitating the planned future self-sustained missions to the Moon or Mars.

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. 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 theese 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 involce diode saturation current, series resistance, ideality factor, shunt resistance and the photocurrent (PV generated electricity). Many numerlical as well as analytical approaches has been developed to simulate mutual interdependence of the solar cell characterizing parameters. Altough the I-V relationship (referred to as I-V curve) is highly non-linear for solar cells which caused problems for many algorithms. Further more 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 similuated 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 optimisation 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 minimised 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

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 availibility 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 Clean Power Research, Federal, State and local authorities as well as relevant utility websites.
- 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. The concept involves a SETO 2020 project with principal investigator Ram Rajagopal of Stanford University.

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

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 optimised 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 at:

- https://github.com/carbon-intensity/methodology/raw/master/Carbon%20Intensity%20Forecast%20Methodology.pdf
- https://github.com/carbon-intensity/methodology/raw/master/Regional%20Carbon%20Intensity%20Forecast%20Methodology.pdf

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 concept involves a SETO 2020 project with principal investigator Yang Weng from Arizona State University.

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. The concept involves a SETO 2020 project with principal investigator Hao Yan from Arizona State University.

5.6. AI for increasing the smart grid awareness

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. The concept involves a SETO 2020 project with principal investigator Cody Smith of Camus Energy.

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. 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. The concept involves a SETO 2020 project with principal investigator Roger French of Case Western Reserve University.

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

Another area of AI application for PV 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. The concept involves a SETO 2020 project with principal investigator Rui Yang of National Renewable Energy Laboratory.

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

This aspect of AI application assisting smart PV 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. The concept involves a SETO 2020 project with principal investigator Wenyuan Tang of North Carolina State University.

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. 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. The concept involves a SETO 2020 project with principal investigator Ali Abur of Northeastern University.

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 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. The proposed concept of variational recurrent model-based net-load prediction algorithms that is currently under validation of the real-world industry and utility data involves another SETO 2020 project with principal investigator Soumya Kundu of the Pacific Northwest National Laboratory.

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. The concept of related CSP AI applications involves a SETO 2020 project with principal investigator Michael Wagner of University of Wisconsin-Madison and may be generalized to concentrator PV.

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.

6. AI assisted smart PV related devices and processes

6.1. Intelligent hybrid inverter / smart-grid inverter

An inverter is a power electronic device or circuit that converts direct current (DC) to alternating current (AC). The resulting AC frequency depends on the particular device used. Inverters are the opposite of converters, which were originally electromechanical devices that converted alternating current into direct current. The input voltage, output voltage and frequency as well as the total power depend on the design of the respective device or the respective circuit. The inverter is not generating any electricity on its own. The power is supplied via the direct current source. An inverter is entirely electronic, in the past it was implemented as combination of mechanical effects (involving rotating device) and electronic circuitry. Static inverters do not use any moving parts during the conversion. Inverters are mainly used in electrical applications where high currents and voltages are present. Circuits that perform the same function for electronic signals (that typically have very low currents and voltages) are called oscillators, while the circuits that perform the opposite function, converting alternating current to direct current for electronic signals, are called rectifiers.

Solar panels produce direct current at a voltage that depends on module design and lighting conditions. Modern modules using 6-inch cells typically contain 60 cells and produce a nominal 24-30 V. (so inverters are ready for 24-50 V). For conversion into AC, panels may be connected in series to produce an array that is effectively a single large panel with a nominal rating of 300 to 600 VDC. The power then runs to an inverter, which converts it into standard AC voltage, typically 230 VAC / 50 Hz or 240 VAC / 60 Hz. The main problem with the "string inverter" approach is the string of panels acts as if it were a single larger panel with a max current rating equivalent to the poorest performer in the string. For example, if one panel in a string has 5% higher resistance due to a minor manufacturing defect, the entire string suffers a 5% performance loss. This situation is dynamic. If a panel is shaded its output drops dramatically, affecting the output of the string, even if the other panels are not shaded. Even slight changes in orientation can cause output loss in this fashion. In the industry, this is known as the "Christmas-lights effect", referring to the way an entire string of series-strung Christmas tree lights will fail if a single bulb fails. However, this effect is not entirely accurate and ignores the complex interaction between modern string inverter maximum power point tracking and even module bypass diodes. Shade studies by major microinverter and DC optimizer companies show small yearly gains in light, medium and heavy shaded conditions- 2%, 5% and 8% respectively- over an older string inverter. Additionally, the efficiency of a panel's output is strongly affected by the load the inverter places on it. To maximize production, inverters use a technique called maximum power point tracking to ensure optimal energy harvest by adjusting the applied load. However, the same issues that cause output to vary from panel to panel, affect the proper load that the MPPT system should apply. If a single panel operates at a different point, a string inverter can only see the overall change, and moves the MPPT point to match. This results in not just losses from the shadowed panel, but the other panels too. Shading of as little as 9% of the surface of an array can, in some circumstances, reduce system-wide power as much as 54%. However, as stated above, these yearly yield losses are relatively small and newer technologies allow some string inverters to significantly reduce the effects of partial shading. Another issue, though minor, is that string inverters are available in a limited selection of power ratings. This means that a given array normally up-sizes the inverter to the next-largest model over the rating of the panel array. For instance, a 10-panel array of 2300 W might have to use a 2500 or even 3000 W inverter, paying for conversion capability it cannot use. This same issue makes it difficult to change array size over time, adding power when funds are available (modularity). If the customer originally purchased a 2500 W inverter for their 2300 W of panels, they cannot add even a single panel without over-driving the inverter. However, this over sizing is considered common practice in today's industry (sometimes as high as 20% over inverter nameplate rating) to account for module degradation, higher performance during winter months or to achieve higher sell back to the utility. Other challenges associated with centralized inverters include the space required to locate the device, as well as heat dissipation requirements. Large central inverters are typically actively cooled. Cooling fans make noise, so location of the inverter relative to offices and occupied areas must be considered. And because cooling fans have moving parts, dirt, dust, and moisture can negatively affect their performance over time. String inverters are quieter but might produce a humming noise in late afternoon when inverter power is low.

An intelligent hybrid inverter or smart grid inverter is a conceptual development of inverters for solar energy applications in which renewable energy is used for self-consumption, especially in photovoltaic solar systems. Earliest devices of this type have been in use since the 1990s. Electricity from solar panels is only generated during the day, with peak generation occurring around noon. Generation fluctuates and may not be synchronized with the power consumption of a load. In order to bridge this gap between what is produced and what is consumed in the evening when there is no solar power production, it is necessary to store energy for later use and to store and consume energy with smart hybrid inverters (smart grid inverters). With the development of systems that include renewable energy sources and rising electricity prices, private companies and research laboratories have significantly improved intelligent inverters to synchronize energy generation and consumption. The function of the intelligent hybrid inverter enables selection and alignment of renewable energy generated by the PV installation , energy from the grid and energy storage based on consumption levels. In contrast to conventional inverters, hybrid inverters do not systematically store energy and send it to the grid instead of systematically storing it in batteries (with a significant yield loss of at least 20%), e.g. when there is more electric power production than consumption. This system also enables the selection of whether electricity from photovoltaic modules is to be stored or consumed via an internal control unit in intelligent devices. This is possible through a technique that adds different energy sources (phase coupling: on-grid or grid-tie techniques) and the management of the electricity stored in the battery (off-grid technology). Hybrid inverters therefore work both on-grid (grid-connected) and off-grid, hence these are referred to as hybrid (both on-grid and off-grid architecture), as well as managing backup (in the event of a power failure). Intelligent inverters are the future of photovoltaic solar module systems that are dedicated to self-consumption of energy or automatic energy consumption and production management, changing consumers into prosumers.

The technology of intelligent hybrid inverters is developed in two directions: i.e. battery based off-grid inverters being further developed for on-grid connection (sometimes also referred to as multi-mode inverters), grid tie inverters being further developed for diverting energy to and from batteries

In the use in off-grid mode (without a network) with the ability to connect to a generator, the inverter must be connected to a battery bank and have real off-grid functions. Not all hybrid inverters can be used in off-grid applications. The use in on-grid or grid-tie (connected to the network) with the possibility of selling energy or excess energy, requires to adhere to the security norm compliance for protection and decoupling (DIN VDE 0126.1). Use in hybrid mode the inverter functions with a battery bank, but is also connected to the grid. This dual functionality is the highlight of hybrid inverters that hence enable energy management (smart grid functionality). If the inverter is used in backup mode, or storage mode it prevents blackouts by switching from on-grid mode to off-grid mode at the moment of a grid outage, thereby eliminating network cuts.

A solar micro-inverter, or microinverter, is a plug-and-play device used in photovoltaics, that converts direct current (DC) generated by a single solar module to alternating current (AC). Microinverters contrast with conventional string and central solar inverters, in which a single inverter is connected to multiple solar panels. The output from several microinverters can be combined and often fed to the electrical grid. Microinverters have several advantages over conventional inverters. The main advantage is that they electrically isolate the panels from one another, so small amounts of shading, debris or snow lines on any one solar module, or even a complete module failure, do not disproportionately reduce the output of the entire array. Each microinverter harvests optimum power by performing maximum power point tracking (MPPT) for its connected module. Simplicity in system design, lower amperage wires, simplified stock management, and added safety are other factors introduced with the microinverter solution. The primary disadvantages of a microinverter include a higher initial equipment cost per peak watt than the equivalent power of a central inverter since each inverter needs to be installed adjacent to a panel (usually on a roof). This also makes them harder to maintain and more costly to remove and replace. Some manufacturers have addressed these issues with panels with built-in microinverters. A microinverter has often a longer lifespan than a central inverter, which will need replacement during the lifespan of the solar panels. Therefore, the financial disadvantage at first may become an advantage in the long term. A power optimizer is a type of technology similar to a microinverter and also does panel-level maximum power point tracking, but does not convert to AC per module.

6.2. AI assisted maximum power point tracking (MPPT)

Maximum Power Point Tracking (MPPT) is a technique in PV solar systems to assure most efficient generation of electricity in regard to external and internal conditions..

PV solar systems exist in many different configurations in regard to their relationship with inverter systems, external grids, battery banks, or other electrical loads. Regardless of the destination of solar energy, the key problem MPPT addresses is that the efficiency of energy transfer from the solar cell depends on the amount of sunlight falling on the solar panels, the temperature of the solar panel, and the electrical properties of the charge. As these conditions vary, the load characteristic that gives the highest power transfer efficiency changes. The efficiency of the system is optimized when the load characteristic changes in order to keep the power transmission at the highest efficiency. This load characteristic is known as the Maximum Power Point (MPP). MPPT is the process by which this point is found and the load characteristic is maintained there. Electrical circuits can be designed in such a way that they present any loads to the photovoltaic cells and then adapt the voltage, current or frequency to other devices or systems. MPPT solves the problem of choosing the best load to be presented to the cells in order to get them the most usable power supply. Solar cells have a complex relationship between temperature and total resistance that creates a non-linear output efficiency that can be analyzed using the I-V curve. The aim of the MPPT system is to sample the power of the PV cells and apply the correct resistance (load) in order to achieve maximum performance under certain environmental conditions. MPPT devices are typically integrated into a power converter system that provides voltage or current conversion, filtering, and regulation to drive various loads, including power grids, batteries, or motors.

Solar inverters convert DC power to AC power and may contain MPPT: These inverters measure the output power (I-V curve) of the solar modules and apply the correct resistance (load) to get the maximum output. The power at the MPP is the product of the MPP voltage and the MPP current.

PV cells have a complex dependence between outside conditioning parameters and output in terms of efficiency of solar energy conversion. The fill factor (FF) is a specific parameter which characterizes the non-linear electrical behavior of the solar cell.

The fill factor is defined as the ratio of the maximum power from the solar cell to the product of open circuit voltage and short-circuit current. Upon tabulated data it is often used to estimate maximum power that a cell can provide with an optimal load under given conditions (power is equal to multiplication of the fill factor and the open circuit voltage and the short circuit current).

Usually the FF along with the open circuit voltage and the short circuit current constitute sufficient empirical data to provide a model of electrical behavior of the PV cell under standard external conditions. In any given operational external conditions, PV solar cell has a unique operating point in which values of the voltage and current result in a maximum power generated. Such values correspond to a certain load resistance which is equal to voltage divided by the current under the Ohm's law. The power generated is voltage multiplied by current. For a PV cell an I-V curve can be plotted, and for the majority of this curve PV cell acts as a constant current source.

There is also a so called MPP region in which the curve has an inverse exponential (approximately) relationship for the interdependence of voltage and current. The power (either input or output from/to the device) is optimized when the derivative of current over voltage (which on the graph of the I-V curve can be interpreted as its slope) is equal the opposite of the current to voltage ratio (at derivative of power over voltage equal zero, i.e. at the so called maximum power point MPP, on the graph interpreted as a knee of the curve). A load with resistance equal to inverse of the ratio of voltage to current draws the maximum power from the cell (defining the so-called characteristic resistance of the PV device). The characteristic resistance is however a dynamic quantity dependent on insolation, temperature, degradation of the cell, etc. If the actual resistance deviates from the characteristic resistance the power output will be diminished which translates to the PV cell not operating efficiently. The process of maximum power point tracking (or device known as MPPT, or a tracker) uses different approaches in electronic control circuitry to allow for the converter to draw the maximum power that can be drawn, by tracking this point with various methods (e.g. bisection method, however only applicable where the full power-voltage curve is available, while in other cases algorithmic approaches are used, recently investigating modern AI methods).

AI application for MPPT is usually with frequent sampling PV panel voltage and current to adjust the duty ratio in an optimal way for reaching maximal efficiency. Impedance as a characteristic of a PV panel is coupled with a duty ratio of a DC-DC converter (a direct current to direct current converter is referred to as a power optimizer, working with a DC solar panel) transforming impedance of a source circuit to the load circuit (directly connecting load to a solar panel will most certainly miss with the operating point of a solar panel the peak intensity. With varying of the duty ratio impedance is changed as well, and in a particular its value (translating into a corresponding duty ratio) the operating point will take the highest power transfer point. Since however the current-voltage curve of a solar panel (or a module) varies significantly with external factors (such as insolation and temperature) it is not possible to fix the duty ratio in order to set the MPP, hence I-V sampling is required and support of conventional statistical or modern AI algorithms (which is referred to as MPPT). In sampling approach optimizing adjustments to the duty ratio are continuously implemented. Sometime microcontrollers are employed to implement all relevant algorithms, however modern implementations usually use external processing power for analytics and load forecasting (especially in a proper integration with a smart power grid). The main methods used for the MPPT and holding a potential to AI methods based improvements are:

- Perturb and observe
- Incremental conductance
- Current sweep
- Constant voltage
- Temperature method

6.3. Smart PV module

Smart modules are a type of solar panel that has a power optimizer embedded into the solar module at the time of manufacturing. Typically the power optimizer is embedded in the junction box of the solar module. Power optimizers attached to the frame of a solar module, or connected to the photovoltaic circuit through a connector, are not properly considered smart modules. Smart modules are different from traditional solar panels because the power electronics embedded in the module offers enhanced functionality such as panel-level maximum power point tracking, monitoring, and enhanced safety.

A power optimizer is a DC to DC converter technology developed to maximize the energy harvest from solar photovoltaic or wind turbine systems. They do this by individually tuning the performance of the panel or wind turbine through maximum power point tracking, and optionally tuning the output to match the performance of the string inverter (DC to AC inverter). Power optimizers are especially useful when the performance of the power generating components in a distributed system will vary widely, such as due to differences in equipment, shading of light or wind, or being installed facing different directions or widely separated locations.

Power optimizers for solar applications can be similar to microinverters in that both systems attempt to isolate individual panels in order to improve overall system performance. A smart module is a power optimizer integrated into a solar module. A microinverter essentially combines a power optimizer with a small inverter in a single enclosure that is used on every panel, while the power optimizer leaves the inverter in a separate box and uses only one inverter for the entire array. The claimed advantage to this "hybrid" approach is lower overall system costs, avoiding the distribution of electronics.

6.4. Smart grid

There are many parallel definitions of smart grids. It is mainly because the smart adjective is not a well-defined concept for devices. In general terms smart grids can be thought of as modernized power grids that make it much more flexible, interactive and automatically manageable upon processed data on its operation parameters in a real time feedback, also including technologies for intelligent monitoring, control, communication, O&M and self-healing.

Majority of the current power grid infrastructure internationally dates back to the 1960s or 50s. The electric installations naturally reach their end of operations and are under an increased stress of a constant electric demand growth. The main drive for smart grids is in integration of renewable energies which due to their fluctuating nature of production impose extreme infrastructure stresses in productions peaks that the smart grid must accommodate and store in excess being sufficiently flexible. Intelligent systems, including self-accommodation, monitoring, control, communication and self-healing technologies help to deal with the diverse network requirements. It is also must involve ease of connection and operation of generators of different sizes, especially enabling small sized generation from small-scale residential PV installation and other small to medium scale distributed renewable energy sources (as well as be able to contain the generated power fluctuations in order to deliver electrical energy in a continuous manner as a just-in-time end-product). The latter aspect is especially important in terms of developing AI assisted smart PV to enable interconnection with a grid in a way that is able to compensate for either deficiency or surplus of the generated energy in regards to the consumption needs (and a general intermittency of the PV energy, generated only by day and in magnitude directly proportional to the determined by the weather solar irradiation level). Smart grids also feature security protocols involving avoidance or minimizing fluctuations in performs and overall failures to deliver electricity in a sustainable, efficient and safe manner.

A widely used definition of the smart grid that stipulates seven key characteristics is defined by the standardization organization International Electrotechnical Commission (IEC). According to this definition, a smart grid must:

- Heal itself, by using real-time information from sensors with automated control to detect and respond to system problems by automatically avoiding or mitigating power outages, power quality problems, and service disruptions;
- Support all generation and storage entities in accommodating power loads with seamless interconnection between distributed power sources;
- Stay resilient to cyber-attacks and natural disasters using technologies to identify and respond to man-made or natural disruptions and isolate the affected areas or redirect power flows around any damaged facilities;
- Enable higher penetration of power generation sources and support larger amounts of renewable intermittent energy resources;
- Optimize assets, utilization, and operational efficiency while minimizing operations and maintenance costs;
- Provide a high-power quality, and saving money by reducing downtimes;
- Enable new services, products, and enable an energy market potential for small-scale generation for local markets (for example) or different utilities services.

All the different elements of the system should communicate with a common interface (in order to reduce the need for translators and assure optimal and timely control message exchange). The smart grid should identify what information is fundamental, which systems need to communicate and how this information needs to be routed, while on the physical level the smart grid should decide how information needs to be transported in a network environment.