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Photovoltaics: cells, modules & systems – a review

Abstract

An overview of photovoltaics, from cells to modules to systems, is presented. Various solar cell structures that have been commercially pursued over the years, as well as emerging solar cell technologies, are described. Approaches to cell-to-module manufacturing are discussed. The influence of temperature on cell/module performance and methods to mitigate it are briefly addressed. This is followed by a discussion of the variety of models and software tools that are being practiced in the industry today for simulation of solar photovoltaic systems. The capabilities, assumptions, limitations, costs, and licensing approaches of selected software tools are compared. An exploration of the use of Machine Learning (ML) techniques to perform: (a). detection of defects at the cell & panel level, (b). estimation of faults and voltage regulation at the PV system level, and (c). performance enhancement and forecasting at the cell and panel level, is presented based on existing studies. The increasing role of PV systems in distributed energy applications including microgrids and growing electricity demand from Data Centers, Electric Vehicle Charging Stations, and other energy-intensive applications, is examined. Opportunities and limitations associated with the development and increased utilization of PV technologies and software tools are presented.

Keywords: solar photovoltaics, solar cells, solar modules, influence of temperature, machine learning techniques, thermal management, microgrids

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Abbreviations: AI, artificial intelligence; API, application programming interface; a-Si:H, hydrogenated amorphous silicon; BSF, back surface field; CRM, customer relationship management; c-Si, crystalline silicon; CSP, concentrating solar power; DC, direct current; DERs, distributed energy resources; DERMS, distributed energy resource management systems; DHI, diffuse horizontal irradiance; DL, deep learning; DNI, direct normal irradiance; DRL, deep reinforcement learning; DTN, data transmission network; ELM, extreme learning machines; EMS, energy management systems; EVs, electric vehicles; FAST-DERMS, federated architecture for secure and transactive distributed energy systems; GA, genetic algorithms; GHI, global horizontal irradiance; GRU, gated recurrent unit; GRNN, general regression neural networks; HJT, heterojunction technology; IR, infrared; KNN, k-nearest neighbors; KUSUM, Kisan Urja Suraksha Evam Utthaan Mahabhiyan; LiDAR, light detection and ranging; LSTM, long short-term memory; MAS, multi-agent systems; ML, machine learning; MPP, maximum power point; MPPT, maximum power point tracking; NREL, National Renewable Energy Laboratory; NLR, National Laboratory of the Rockies; NWP, numerical weather prediction; OPVs, organic photovoltaics; PERC, passivated emitter rear contact; PSCs, perovskite solar cells; PSO-ELM, particle swarm optimization with extreme learning machine; RF, random forest; RL, reinforcement learning; ROI, return on investment; RNN, recurrent neural network; SEIA, Solar Energy Industries Association; SaaS, software-as-a-service; SAM, System Advisor Model; SCADA, supervisory control and data acquisition; SVM, support vector machine; TMY, typical meteorological year; TOPCon, tunnel oxide passivated contact; UI, user interface; US, United States; USDOE, United States Department of Energy; USEIA, United States Energy Information Administration

Introduction

With the growing demand for energy across the world, renewable energy sources have begun to contribute considerably towards this effort. The United States Energy Information Administration (USEIA) projects a nearly 50 percent increase in global energy consumption by 2050 with fossil fuels still being the dominant form of energy.[1]. By 2050, the USEIA also forecasts a significant increase in renewable energy usage that will almost match the amount of energy consumed via fossil fuels.[1] According to Solar Energy Industries Association (SEIA), PV systems could generate up to 16 percent of the world's electricity by 2050 while Concentrating Solar Power (CSP) plants could add another 11 percent.[2] However, this implementation will require solar panel manufacturing technologies that will yield reliable and cost-effective approaches to installed dollar per watt for solar terrestrial applications and modules that are light weight, radiation and charged particle tolerant for space applications, with at least 25-year life expectancy.

A critical factor in a PV system's performance is MPPT, Maximum Power Point Tracking, which is the process of adjusting the electrical load to maximize the power output of the system. Another key parameter is the amount of solar irradiance received by the system over a period as this affects how much light energy can be converted into usable electricity by the PV system. Consequently, partial shading conditions can reduce solar irradiance, and are caused by obstructions such as clouds, buildings etc. on the PV system. High temperatures can reduce PV performance because increasing cell temperature generally lowers voltage and power output. The PV system's orientation and tilt angle can have a major impact on energy yield and should be selected based on site conditions, latitude, shading, roof constraints, and the desired seasonal output. Considering electrical components, an efficient inverter is essential to convert the Direct Current (DC), generated by the PV system, into Alternating Current (AC) which is then used to power homes, buildings etc. via the grid.

Like any other technology, frequent maintenance and upkeep is important for a PV system to run smoothly and effectively for long periods of time. There can be several reasons for maintenance of a PV system which include soiling, cracks in the PV array, faulty inverters, islanding, and numerous other issues that can lead to major problems. Due to this, Machine Learning (ML) models can be used to monitor, classify, and assess some PV system faults and operating conditions alongside conventional monitoring methods.

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As a result of the problems stated above, numerous solutions using ML methods have been developed and iterated upon to solve specific and/or general problems regarding PV systems. ML methods are increasingly being studied alongside statistical and physics-based approaches for solar irradiance and PV power forecasting. A recent review reported by Gaviria et al. summarizes ~ 100 research articles' key findings relating to ML methods.[3] Narvaez et al.[4] analyzed Encoder-Decoder LSTM (Long Short-Term Memory) and GRU networks for daily and weekly time horizon predictions which showed that the LSTMs outperformed the GRU networks. In a study conducted by Ahn and Park, they utilized a Recurrent Neural Network (RNN) as a forecaster for PV power output. The experiment conducted showed that the RNN method obtained higher prediction accuracy than the comparison models evaluated in that study.[5] Hossain and Mahmood developed a LSTM, a type of RNN method and used it in conjunction with a K-means algorithm to sort irradiance data into various sky groups. Hossain and Mahmood reported that this model outperformed the comparison RNN, General Regression Neural Network (GRNN), and extreme learning machine (ELM) models used in their study.[6] Several studies show the potential of LSTMs for irradiance forecasting due to their ability to capture time-series dependencies in weather patterns.

In order to solve the problem of MPPT under partial shading conditions, researchers have started to move away from conventional algorithms like perturb and observe because they can become trapped at a local maximum. Instead, researchers have investigated techniques such as Reinforcement Learning (RL) algorithms to obtain the Maximum Power Point (MPP). For instance, Kalogerakis et al. utilized a tabular Q-learning algorithm to track the MPP under partial shading conditions.[7] The results obtained were compared to a particle swarm optimization algorithm and showed that the RL method reduced the time needed for detecting MPP with respect to other RL algorithms in the range of 80.5 % to 98.3 %.[7] Avila et al.[8,9] proposed a deep learning (DL) model-free algorithm based on RL using an OpenAI Gym environment. The reported results showed that the algorithm was able to operate within less than 1 % of the theoretical MPP. These studies indicate that RL-based methods can be effective for MPPT under partial shading conditions.

Numerous ML techniques and algorithms have been proposed in several papers and researchers continue to counteract the problems in operating PV systems. There is a lack of comparative studies that analyze the performance and capabilities of various software packages available on the market, as well as their limitations and assumptions. As a result of this gap in solar cell ML-related research, this paper aims to study the details of each software package. More specifically, this study will identify the developer/vendor of the software package, its capabilities, assumptions, limitations, costs, and licensing policies.

This paper will be structured as follows: Section 2 will discuss experimental approaches of various solar cell structures, Section 3 presents numerous models used by the industry to improve PV system efficiency and performance, Section 4 compares the various models, and Section 5 presents a conclusion.

Review methodology

This paper follows a scoping review approach since it covers a wide range of topics relating to photovoltaic technologies, software tools, and ML applications rather than focusing on one very narrow research question. The search for sources mainly follows the topics that are discussed throughout the paper. These include: (i) solar cell structures such as PERC, TOPCon, HJT, perovskite, OPVs, tandem solar cells, (ii) PV design software, forecasting, grid integration, maintenance, fault detection, MPPT, and ML methods used in PV systems. Different combinations of these topics are searched along with terms such as photovoltaics, solar cell, efficiency, market share, software, forecasting, DERMS, defect detection, and machine learning. Source Selection Flow used for this review is illustrated in Figure 1.

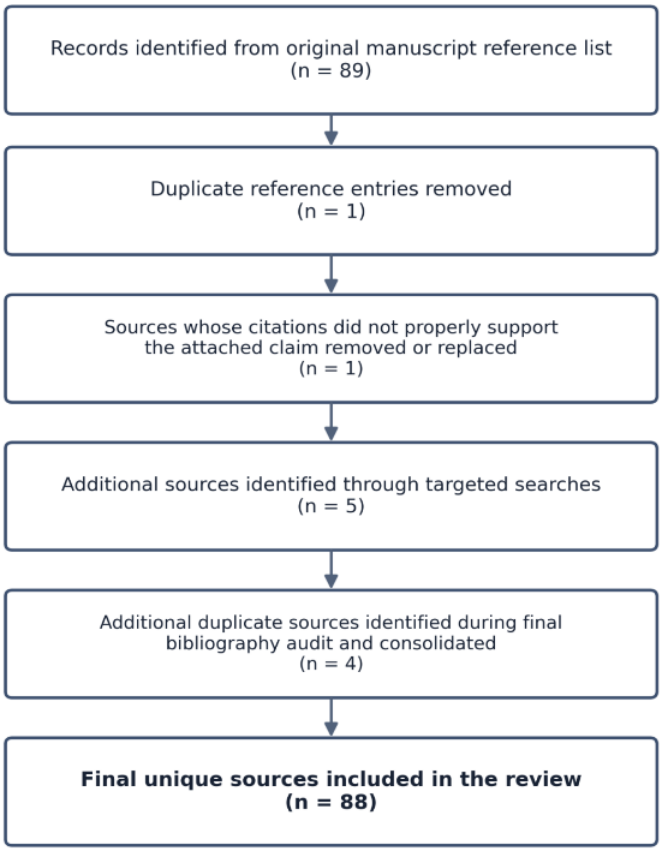

Figure 1 Source selection flow used for this review.

The software tools, discussed in the paper, are compared based on their similarity. These include the developer or vendor, the utility of the tool, its capabilities, assumptions or required inputs, limitations, cost or licensing, and the type of source available to support the information. Since the software tools were not tested against each other using the same dataset or experiment, the comparisons are descriptive rather than a direct quantitative benchmark.

Experimental approaches

As a preamble to discussing the various experimental approaches to the fabrication of solar cell structures, it may be noted that some of the solar cells fabricated in research laboratories have been able to achieve efficiencies of ~ 47 % under concentrated illumination.[10] However, commercially available silicon solar panels, that are most used, have average efficiency in the range of 21-23 %.[11] The PV industry continues to work towards narrowing the gap between cell/module performance specifications in the R&D and commercial sectors. To bridge this gap, new cell/module architectures and methods of processing and fabrication are constantly evolving. This section will present an analysis of the solar cell structures and industry players that are working towards improving the cell/module performance while reducing costs etc. In addition to physical modifications, ML methods that are being practiced in the PV industry are discussed.

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Current landscape: dominant structures, and key players

In order to obtain high efficiency, a solar cell should have a structure which maximizes light absorption while possessing minimum electrode resistance. Loss mechanisms in solar cells can be categorized into four principal physical phenomena. These are as follows: loss through reflection (~4%), thermalization (~30% due to excess photons), recombination (5-20%), and resistive losses (2-5%).[11,12]

Reflection loss occurs when sunlight interacts with a solar panel resulting in 4-8 % of the incident light bouncing off the surface which is ~16-32 W of the incident energy (assuming 400 W Panel). Thermalization loss occurs due to the bandgap mismatch; the bandgap of silicon is 1.1 eV (indirect) implying that photons with energy below 1.1 eV pass through, while high energy photons (UV) lose excess energy as heat. Recombination loss occurs since 5-20 % of the electrons generated do not reach the load; instead, these electrons recombine with holes. There are three main types of recombination loss mechanisms in solar cells. These include the following: bulk recombination (comprehensive; one specific type - Shockley-Read-Hall recombination ≈3-8% loss, present in cells due to defects or traps), surface recombination (2-5% loss, occurs mainly at the nanoscale), and Auger recombination (1-3% loss, prevalent in high efficiency cells). Resistive losses occur due to electrical resistance that exists in the wiring and other electrical components.[11] A visual representation of the loss mechanisms in solar cells is presented in Figure 2.[13]

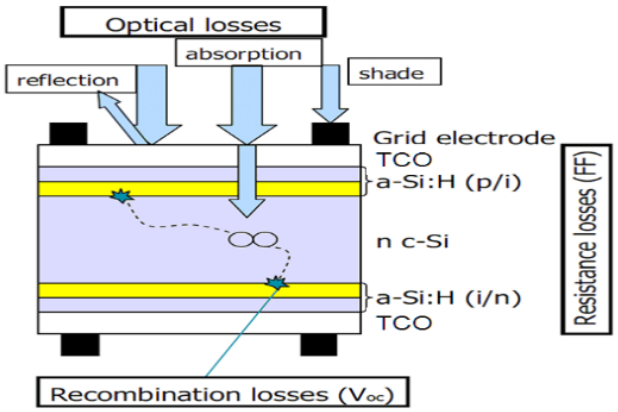

Figure 2 A visual representation of the various loss mechanisms in solar cells. Reprinted from Ling.[13]

Today, three crystalline silicon solar cell structures dominate the PV industry. These are as follows: PERC (Passivated Emitter and Rear Contact), TOPCon (Tunnel Oxide Passivated Contact), and HJT (Heterojunction Technology). These structures represent modifications/advancements to the standard crystalline silicon design. According to the 2025 International Technology Roadmap for Photovoltaics (ITRPV), TOPCon overtook PERC as the dominant crystalline-silicon cell technology by the end of 2024, while HJT remained a smaller share of the market.[14] Historical ITRPV data also show how quickly these market transitions can change. Stefani et al. compared ITRPV projections from 2012 to 2023 with estimated actual market shares, and found that PERC grew faster than many earlier projections while SHJ and some other technologies did not gain market share as quickly as expected.[15] This makes it important to treat market-share projections based on the year they were reported instead of as fixed long-term values.[14,15] Figure 3 shows these historical projections for the main silicon solar cell architectures.[15]

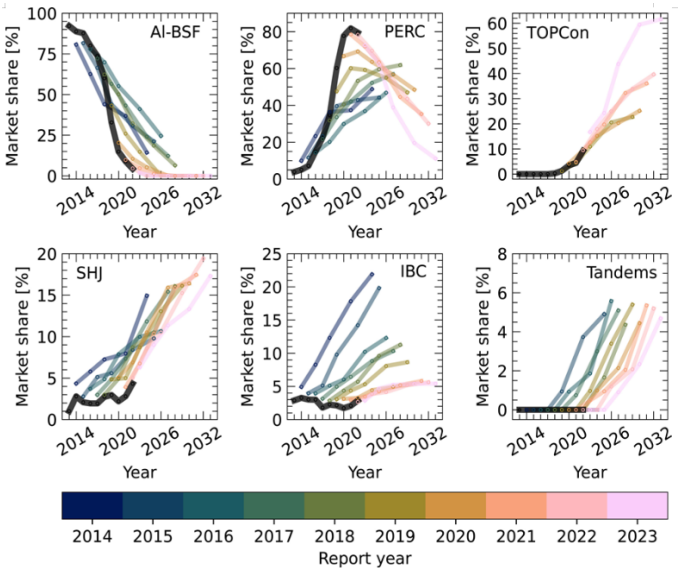

Figure 3 Silicon Solar Cell Architecture Market Projections. Reprinted from Stefani et al.[15]

PERC solar cells are a modified version of Back Surface Field (BSF) architecture. A modification was needed since the rear aluminum side of the cell in BSF reflected only 60-70 % of infrared (IR) light leading to parasitic absorption and unwanted heating.[12,16] Thus, a dielectric passivation layer on the rear side was applied to prevent this and reduce recombination losses on the dark side of the cell.[16] PERC cells usually have efficiency in the range of 18 to 22 %.[12,16] A visual representation of a standard BSF cell versus a PERC cell is shown in Figure 4.[12]

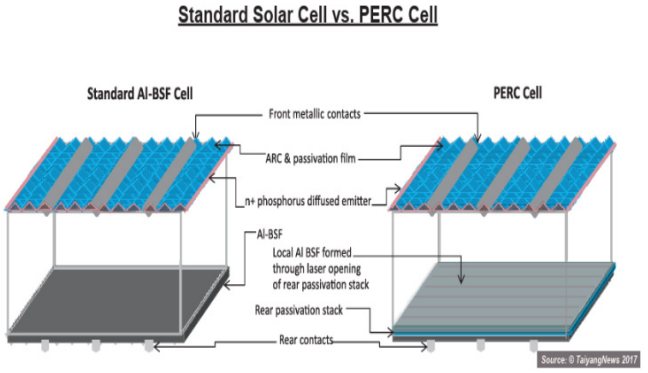

Figure 4 A schematic comparison of standard BSF solar cells VS. a PERC cell. Reprinted from Chunduri, et al.[12]

Processing PERC cells involves a delicate procedure of depositing a rear surface passivation film which is then opened to allow for the formation of rear contacts. Passivation is the process in which defects in the silicon wafer are counteracted to reduce surface recombination of charge carriers to allow for increased efficiency. An ideal rear surface passivation material should have a highly fixed negative charge. Aluminum Oxide perfectly meets these requirements and is the most preferred passivation material for rear surface passivation.[16] A schematic of the processing sequence of PERC cells is shown in Figure 5.

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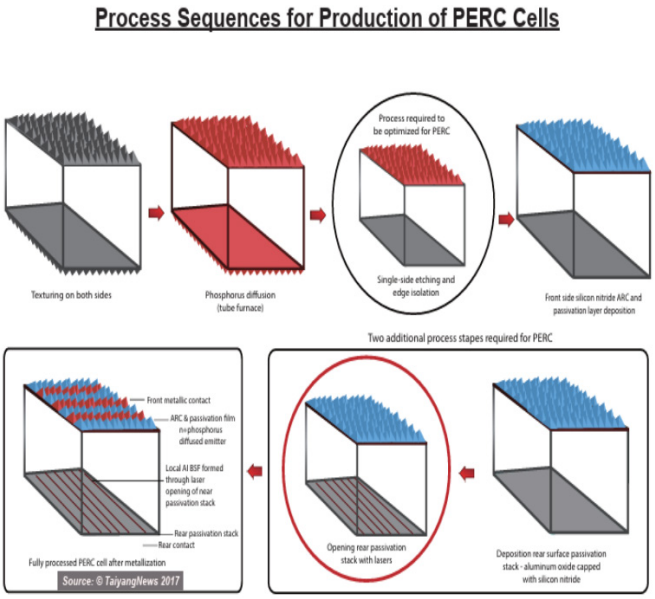


Figure 5 A flowchart of the processing sequence of a PERC cell. Reprinted from Chunduri, et al.[12]

In TOPCon solar cells, the metal does not come into contact with the silicon wafer. Instead, a thin tunneling oxide layer is applied which is followed by a layer of highly doped n or p poly silicon that contacts the rear metal contacts. This oxide layer allows for excellent passivation and reduces losses produced by metal contacts interacting with the semiconductor material.[17,18] TOPCon solar cells have efficiency in the range of ~ 22 to 26.10 %.[18] Figure 6 shows the schematic of a TOPCon solar cell. A flowchart of the fabrication process steps of TOPCon solar cells is shown in Figure 7.[18].

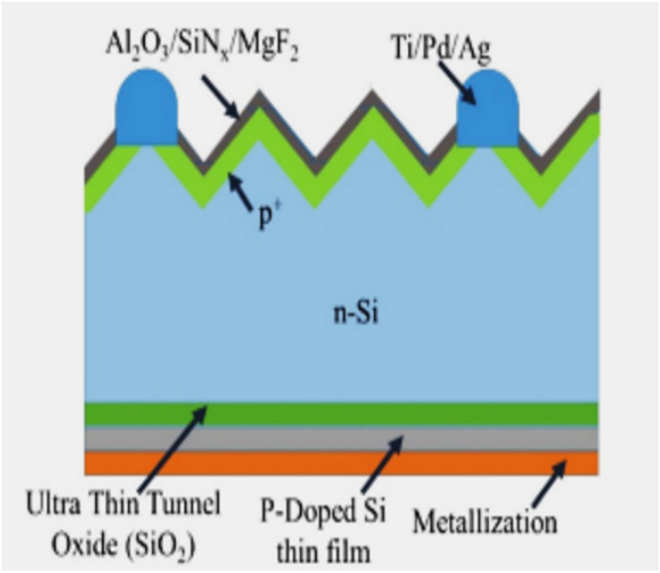
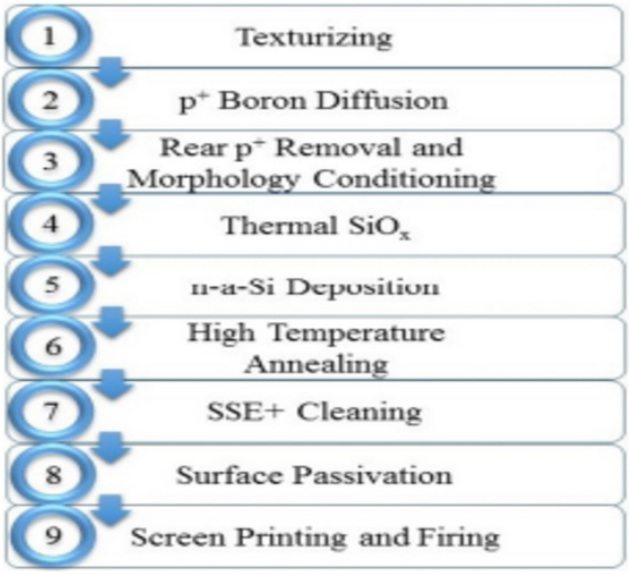


Figure 6 TOPCon solar cell visual diagram. Reprinted from **[18]**.

Figure 7 TOPCon solar cell fabrication process flowchart. Reprinted from Yousuf et al.[18]



HJT solar cells use layers of amorphous silicon (usually 3 layers) to form a junction with crystalline silicon that can provide high efficiencies, and favorable temperature performance.[19-21] The average efficiency of HJT solar cells is in the range of 22-26.70 %.[20] Bifacial HJT cells are fabricated as follows: Undoped amorphous silicon (a-Si:H) layers are deposited on both sides of an n-crystalline silicon substrate which is then followed by a doped a-Si layer for the contact (on both sides) and then covered with transparent conducting oxide layers and silver on both sides.[20,21] Figure 8.[21] presents an illustration of a bifacial HJT solar cell structure. Recent solar cell products include Interdigitated Back Contact (IBC) and Hybrid Passivated Back Contact (HPBC) cells. They represent high efficiency architectures that consist of metal grid lines on the rear side of the cell. Such architectures facilitate in removing front shading, maximizing thereby the light absorption in the cell, thus enhancing cell efficiencies of > 25%.

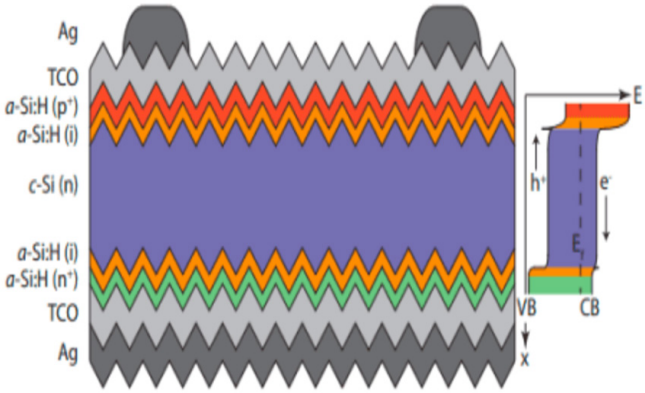


Figure 8 Schematic of a bifacial HJT Solar Cell. Reprinted from DeWolf, et al.[21]

The best cell efficiencies, for a variety of cells, reported from laboratories and research groups, across the world, are summarized in Figure 9. The National Laboratory of the Rockies (NLR; formerly the National Renewable Energy Laboratory, NREL) maintains and supports the database of Best Solar Cell Efficiencies from research laboratories from across the world.[22]

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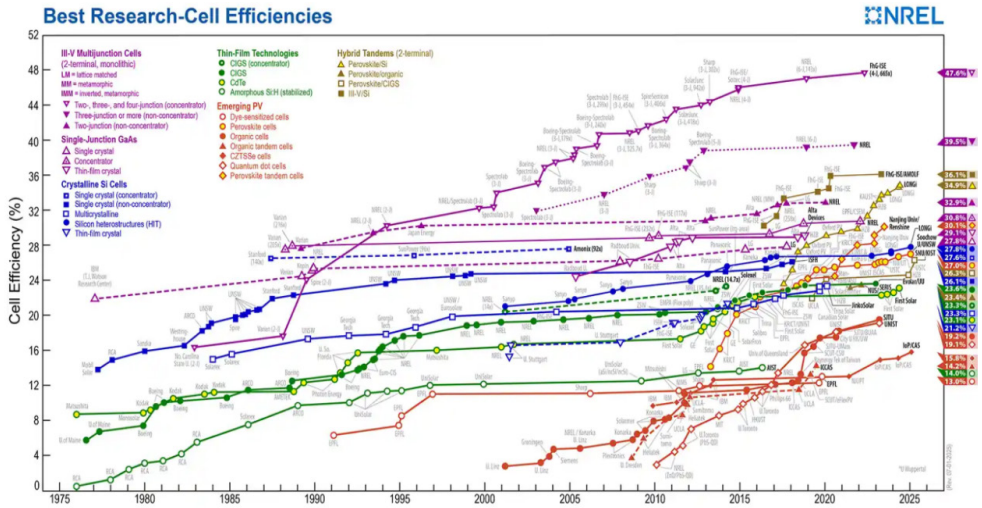

Figure 9 Best research-cell efficiency chart. Reprinted from NLR.[22]

As of July 2026, several key companies remain associated with these solar-cell technologies.[23,24] Many of the largest active companies are headquartered in China, which continues to account for more than 80 percent of global solar-panel manufacturing capacity.[25]. Current product portfolios include LONGi Solar (HPBC 2.0/back-contact), JinkoSolar (TOPCon), Trina Solar (TOPCon), JA Solar (TOPCon), Canadian Solar (PERC, TOPCon, and HJT), Huasun (HJT), and Risen Energy (HJT and TOPCon).[26-33] Panasonic and Meyer Burger are now better treated as historically significant HJT manufacturers rather than major active producers.[31,34] Table 1.[23,24,26-34] compares the current and historically significant companies, and Table 2.[16,18,20,35,36] compares the three major solar cell structure technologies currently on the market.

Table 1 A Comparison table of selected solar cell structure companies, July 2026.

Company	Tech	Representative module efficiency	Status / technology notes	Origin	Warranty
LONGi	HPBC 2.0 / back-contact	21-23% +	Active producer; HPBC 2.0/back-contact portfolio	China	12-15 years
Jinko	TOPCon	21-23% +	Active producer; TOPCon portfolio	China	12-25 years
Trina	TOPCon	20.5-22.5%+	Active producer; TOPCon portfolio	China	15-25 years
JA	TOPCon	21-23% +	Active producer; TOPCon portfolio	China	12 years
Canadian	PERC, TOPCon, HJT	20.5-22%+	Active producer; PERC, TOPCon, and HJT portfolio	Canada/Asia	12-25 years
Panasonic	HJT	21-22.5% +	Historically significant HJT manufacturer	Japan	25 years
Huasun	HJT	22.5-24% +	Active HJT producer	China	15 years
Risen	HJT, TOPCon	22-24% +	Active HJT and TOPCon producer	China	12-15 years
Meyer Burger	HJT	21.5-23.5% +	Historically significant HJT manufacturer	Switzerland/ Germany	25-30 years

Table 2 A Comparison Table of the 3 Major Solar Cell Structures, July 2025. Sourced from.[36]

Feature	PERC	TOPCon	HJT
Advantages	- Mature, lower-cost manufacturing - Widely available - Long commercial track record	- Higher typical efficiency than PERC - Lower degradation potential - Better high-temperature performance than PERC - Can be adapted from modified PERC production lines	- High commercial efficiency - Low degradation rates - Strong high-temperature performance - High bifaciality

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Table 2 Continued..

	- Lower efficiency than TOPCon and HJT	- Higher manufacturing cost than PERC	- Higher manufacturing cost
Disadvantages	- Higher degradation relative to n-type architectures	- More complex processing	- Different and more complex manufacturing process
	- Less favorable high-temperature performance	- Shorter commercial track record than PERC	- Sensitivity to some process and environmental conditions

Technology, efficiency, and warranty values are representative manufacturer-reported specifications from the respective company sources listed in the reference list and are not an independent performance benchmark. Installed-system cost is not compared because it varies substantially with location, installer, financing, incentives, and the system's configuration.

Emerging technologies: the bright future ahead

While traditional solar cell structures such as PERC, TOPCon, and HJT offer established efficiencies with tried and tested methods both in the lab and in the real world, continued research is aimed at improving efficiency, cost, and other performance characteristics while reducing the use of indium and silver. This paper will also look at new forms of solar cell structures that are still being researched and developed. These new structures have their individual drawbacks and limitations, but further research and improved hybrid methods could address some of these challenges. The key emerging new solar cell structures include perovskite solar cells (PSCs), organic PVs (OPVs) and tandem (Multi-junction) solar cells.

Perovskite Solar Cells (PSCs) are more specifically made from "metal-halide perovskites". They are made of organic ions, metals, and halogens. PSCs can be produced using relatively thin absorber layers and potentially low-cost processing routes. Their (wide) bandgaps can be tuned easily and the addition of another absorber layer like silicon (lower bandgap) forms a tandem solar cell (PSC, top cell, captures high energy photons, and silicon cell, bottom cell, captures lower energy photons). According to the United States Department of Energy (USDOE), perovskite-silicon tandem cells have achieved efficiencies of ≈ 34 %.[37] PSCs can also be made flexible which allows for them to be placed on clothing, windows, camping and outdoor gear, wearable and portable electronics etc.[38] However, PSCs are prone to damage in the long run, and are sensitive to light, heat, and voltage.[37, 39] Furthermore, PSCs are known to have stability issues, and are known to lose up to 20 percent of their initial performance as time progresses.[39] Figure 11 shows the overall structure of a PSC, and Figure 12 represents the fabrication process of a PSC.

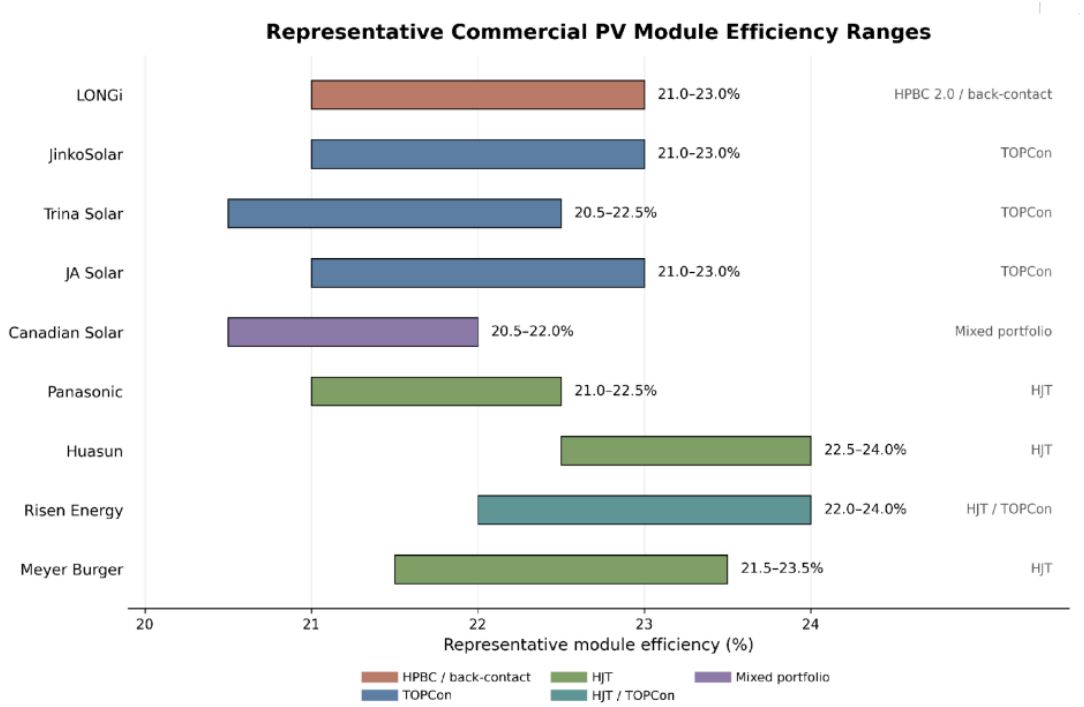

Figure 10 Representative commercial PV module efficiency ranges.

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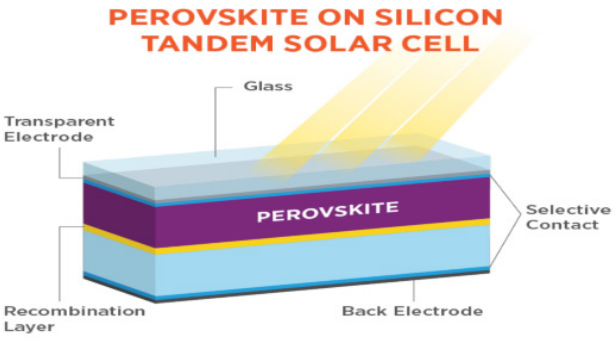

Figure 11 A Visual representation of a PSC. Reprinted from US Department of Energy.[37]

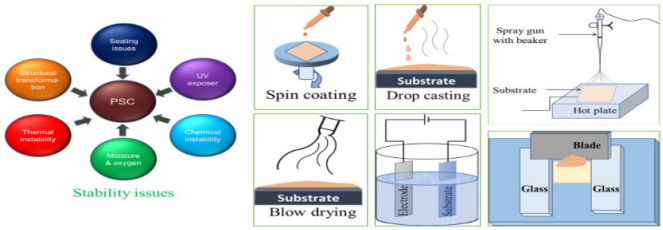

Figure 12 A Diagram of the Fabrication for a PSC, and Problems Faced by PSCs. Reprinted from Chowdhury.[39]

OPVs utilize molecular or polymeric absorbers instead of inorganic absorbers like other conventional routes. The organic absorber is used with an electron acceptor (fullerene is an example) which allows for smooth electron transfer.[40] The process of converting photons to electrons is overall the same as in a standard solar cell. OPVs have relatively lower efficiencies of about 18.2 %. One advantage is that there is a diverse array of organic materials that can be utilized for the absorber and acceptor. OPVs are flexible which allows for them to be put on a variety of surfaces such as clothes, cars, windows etc.[40,41] Additionally, OPVs are very cost effective to manufacture as roll-to-roll processing techniques can make manufacturing easy and scalable. On the other hand, they have relatively low operational lifetimes, and cannot handle high temperatures without damage.[40] Figure 13 shows the overall structure for a general OPV, and Figure 14 represents the fabrication process of an OPV.

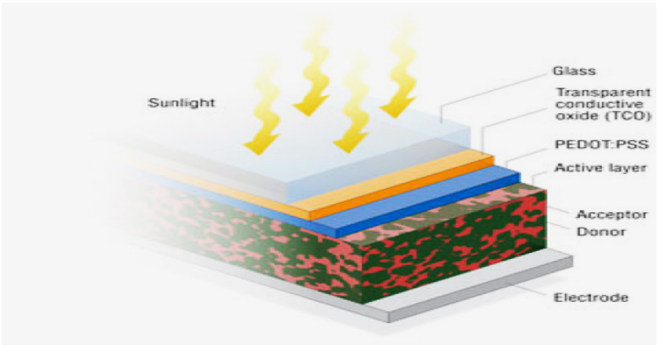

Figure 13 A Visual Diagram for an OPV. Reprinted from US Department of Energy.[40]

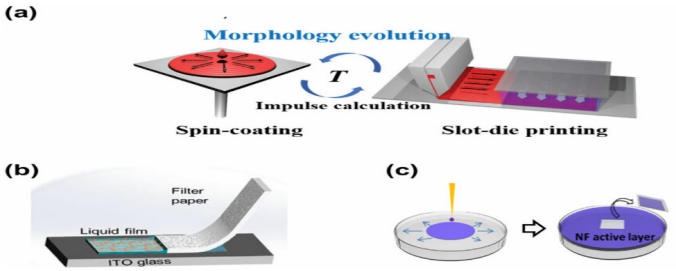

Figure 14 The Fabrication Process Visualization for OPV. Reprinted from Sun L et al.[42]

Multijunction solar cells have achieved the world record for the highest obtained cell efficiencies. In particular, a four-junction solar cell which was developed by the Fraunhofer Institute for Solar Energy Systems (ISE) achieved a 47.6% efficiency under concentrated illumination at 665 suns using gallium indium phosphide (GaInP), aluminium gallium arsenide (AlGaAs), and other materials.[10] This result under concentrated-light should not be directly compared with efficiencies reported under standard one-sun conditions. However, these multijunction solar cells are complex to fabricate due to their complex processes, high costs involved, and fragility.[43] Figure 15 shows a visual representation of a triple junction solar cell, and Figure 16 shows the fabrication process of a flexible triple junction solar cell.

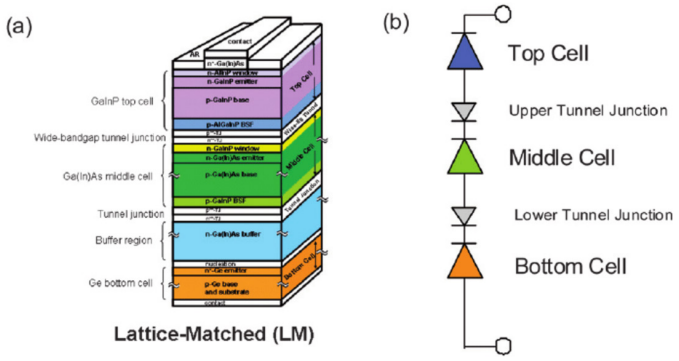

Figure 15 A Visual Representation of a Triple Junction Solar Cell. Reprinted from Cotal H, et al.[44]

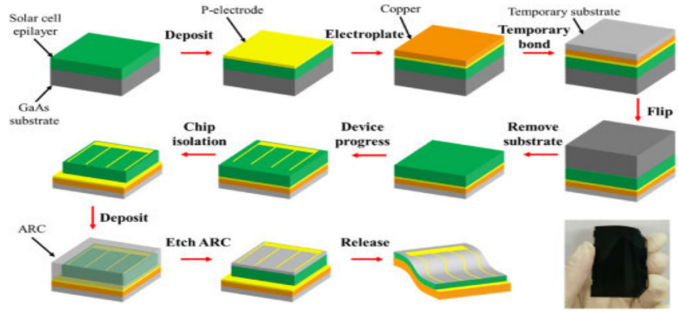

Figure 16 A Visual Representation of the Fabrication Process for a Triple Junction Solar Cell. Reprinted from Luo X, et al.[45]

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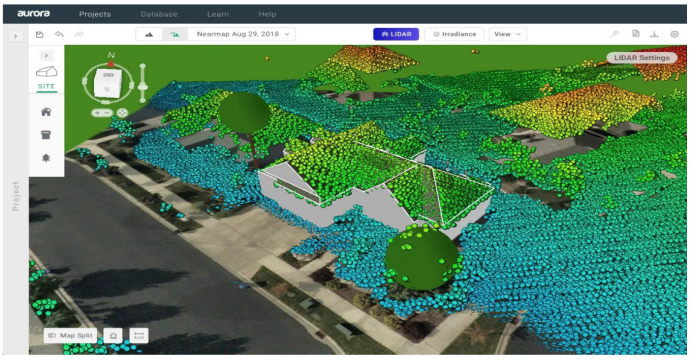

Figure 17 Aurora Solar Software Representation. Reprinted from Aurora Solar.[59]

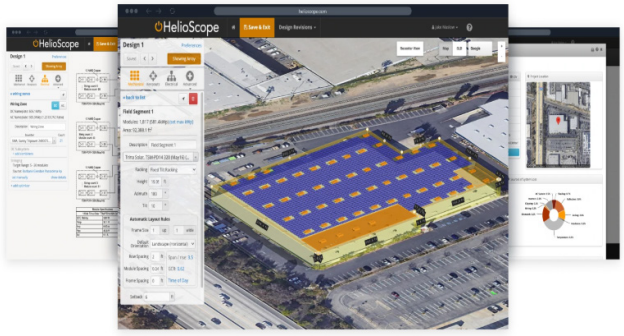

Figure 18 HelioScope Software Representation. Reprinted from HeliScope.[60]

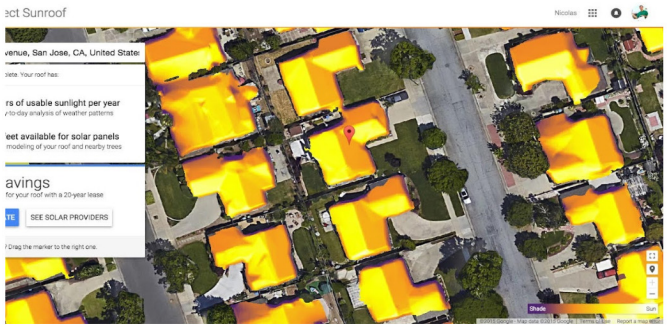

Figure 19 Project Sunroof Software Representation. Reprinted from Google.[69]

Grid independence techniques across the US, China, Taiwan, and India

While centralized grids can provide coordinated control, outages or transmission failures can propagate across interconnected parts of the system. Thus, failures in one part of the grid can affect other regions and disrupt electricity service to communities, cities, and critical infrastructure. For instance, during the Northeast blackout of 2003, about 50 million consumers were affected, and large parts of New York City were severely impacted with power not being restored for 29 hours or up to 4 days in some areas. Furthermore, New York City was not the only part of North America impacted but several other areas in the state of New York, Massachusetts, New Jersey, Michigan, Ohio, Toronto, Ottawa, and Ontario were also impacted.[46] This loss of ~ $10 billion was associated with a cascading grid failure that began after transmission-line problems in Ohio.[47] Events of this scale illustrate the importance of resilience measures that can reduce the duration and geographic reach of outages. Thus, grid-independence and microgrid approaches can be analyzed as options for improving local and regional resilience.

In this connection, Community Solar Programs in states like New Jersey, Massachusetts, and Minnesota are large-scale solar projects in which local residents are allowed to purchase a share of the energy output. These projects allow users to receive credits on their electricity bill based on the production of their share.[48-50] This allows access to solar for those who do not have roofs suited for solar or are limited by local rules, restrictions and guidelines. The utility department manages the billing, and proper connections but the main feature of these projects is the fact that these Community Solar plants are privately or community owned. New Jersey's Community Solar Program also includes requirements intended to expand access for low and moderate-income communities.[48] In a state like California that is often affected by wildfires, The Santa Rita Union School District has implemented microgrids which use solar technology and battery storage solutions to keep schools powered with electricity so they can be transformed into local shelters during a critical emergency. This system works via a PV system and large batteries that are installed on site which can reduce a school's electricity usage and cost during normal operating times. However, when the main connected grid fails, this microgrid has an automated switch to disconnect itself from the main grid and is powered by solar energy and stored battery energy.[51] The strategies and examples mentioned above show how local communities and states can use distributed PV and microgrids to improve resilience and expand access.

For a small island such as Taiwan that is highly dependent on imported fuels and has limited available land, distributed and space-efficient energy systems can support resilience during supply disruptions or natural disasters. Taiwan's size is close to that of Maryland, but has a population that is about 4 times bigger than that of Maryland, and thus, needs a significant amount of energy while maximizing space as much as possible. As a result of this space constraint, Taiwan has integrated large-scale PV projects in counties like Pingtung where solar modules are implemented over farmland.[52] This approach allows for continued farming with minimal disruptions while generating electricity, reducing competition between land use for food and electricity. Furthermore, Taiwan has a floating solar project called The Changhua Coastal Industrial Park that utilizes solar panels on floating structures on man-made reservoirs. This reduces the need to use land that could serve other purposes, and the water can provide a cooling effect that reduces thermal problems in PV modules. This project's energy output is then routed to the industrial park's local grid.[53]

In China, large-scale solar generation is also paired with long-distance transmission infrastructure. For example, the ultra-high-voltage DC transmission link is able to transmit power from the Xinjiang region in the northwest of the country to Anhui province in eastern China, transmitting 12,000 megawatts of electricity over 3,000 kilometers at 1.1 million volts.[54,55] This type of infrastructure allows large amounts of power generated far from load centers to be transferred to eastern regions, which can support grid balancing and energy delivery across long distances.

India has also pursued distributed solar and microgrid approaches to expand electricity access in areas where grid service is limited. Companies like Tata Power and Husk Power Systems have installed microgrids in remote villages where electricity is either non-existent or very limited.[56,57] More specifically, Tata Power reported installing 161 solar microgrids in one year in places like Uttar Pradesh and Bihar, and has stated plans for a much larger rollout.[57]. Furthermore, Husk Power Systems has also built and helped install solar microgrids in Uttar Pradesh and Bihar, and reported 75 microgrids capable of providing 24/7 electricity access. These microgrids can combine a

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relatively small PV system (23-30 kW), battery storage, and a local distribution network that allows homes and businesses to connect to the power supply. Customers can pay through prepaid meters, and the systems can operate separately from the centralized grid. Local workers can also be trained for maintenance and operation.[56] The Indian Government also offers a nationwide program called the Pradhan Mantri Kisan Urja Suraksha Evam Utthaan Mahabhiyan (KUSUM) that assists farmers in installing solar water pumps to replace diesel pumps. KUSUM subsidizes part of the installation cost. Furthermore, if extra electricity is generated by eligible systems, it can be supplied to the local grid under the program structure.[58]

The goal for grid independence is a trend that is starting to increase slowly all around the globe as the need for reliable, secure, and stable electricity becomes more and more important especially with the rise of AI, and their respective data centers. The strategies employed to achieve grid independence can vary greatly from country to country. For instance, China is approaching the issue of grid independence in a way which heavily involves the government to do all of the planning and management, while countries like the US and India offer their citizens the chance to be a part of the move for an independent grid. On the other hand, Taiwan aims to solve the problem of grid independence as soon as possible due to it being a matter of national security for Taiwan which is a result of complicated geopolitical situations while balancing the lack of space available for PV microgrids. The common theme in all of these nations is that PV systems and microgrids are not just another source of renewable energy but are tools designed to empower communities, secure energy production and demand.

Overall, these examples show that as PV systems become more distributed through Community Solar, microgrids, batteries, and other DERs, improving the cell or module itself is only one part of the problem. Forecasting, monitoring, grid coordination and control also become increasingly important as these systems get larger and more interconnected. As a result, software tools and ML/AI methods are becoming more important for the design, management, forecasting and maintenance of PV systems, which will be discussed in the following sections.

Models for simulation

The nameplate rating of a solar cell or a PV system is determined under the controlled environment of a laboratory that is isolated from the rest of the world. However, this ideal rating is just a mere facade because in reality, these PV systems have to endure a constant clash with the nature of the environment around them. Whether it be grueling summer heat, gargantuan clouds, or ferocious storms of dust, or hail storms, PV systems have to face it all while balancing optimal power output. Thus, it is vital to model these complex interactions, and use ML methods/software to effectively design PV systems that are durable, robust, and are capable of providing maximum power with minimal disturbance. Traditionally, researchers, and engineers would need to solve complicated physics equations that would take an enormous amount of time to model these interactions, and develop solutions for them. However, a paradigm shift is occurring in the solar cell market, and that is the introduction of ML methods, and software for forecasting, maintenance, and optimal power output. This section will focus on several models available on the market that are allowing for efficient PV system management and operation.

Descriptions of commercial software capabilities in Sections 3 and 4 are based primarily on the cited vendor documentation unless a peer-reviewed, government, or laboratory source is specifically cited. These descriptions report stated capabilities and should not be interpreted as independent validation.

Machine learning & artificial intelligence for pre-construction and optimization

The core challenges during the pre-construction, and optimizing system design stage are numerous, and to ensure maximum lifetime value, several factors have to be considered. These factors include shading conditions of a region throughout the year, roof geometries, choice of equipment, weather patterns etc. Traditionally, this would require manually going to the site, inspecting it, drafting complicated reports, and performing physical measurements/calculations. However, with the advent of recent AI, and ML softwares/methods, this long, and complicated process has turned into a more efficient and accurate process that leads to better system optimization while saving time and money.

Aurora Solar is a software-as-a-service (SaaS) company which provides a cloud-based platform for solar energy system installation. Aurora Solar brings several parts of the process such as design, sales, permits and installation, into one platform. For example, Aurora Solar can generate 3D models of buildings using aerial imagery and LiDAR data which can then be used for shading analysis while accounting for obstructions. This tool can estimate a PV system's energy output by taking into account factors such as degradation rates, inverter efficiency, irradiance input and local weather data.[59]

Another key software tool is HelioScope which is known to be tailored for commercial, and industrial projects, but is still capable of handling residential projects.[60] HelioScope was acquired by Aurora Solar in 2021, and this has lead to these two software tools being widely used commercial tools in the market.[61] HelioScope gives the user the ability to design full PV systems in a very short amount of time by allowing for layouts of modules on roofs, carports, and ground sites while allowing for parameter adjustments like azimuth, tilt angle, row spacing, racking types, etc. HelioScope can also offer shading analysis, much similar to Aurora Solar, by turning the building into a 3D model, and taking obstructions into account. However, the major strength of the HelioScope software is its ability to compute the energy output of a full PV system on an hourly basis for one full year while accounting for the specific characteristics of the chosen module, and inverter.[60] This tool also takes into account electrical losses, soiling, module mismatches, and several other factors based on user input while being within 1 percent of PVsyst (An industry standard benchmark for energy output simulation).[62] HelioScope is accessible via any web browser which reduces the necessity to install the software and also leads to easier collaboration if working with a team.[60]

RatedPower is another SaaS platform that is primarily designed to optimize the design of utility-scale PV plants for larger scale applications. RatedPower has several key features that streamline the engineering process for large scale plant layouts. In particular, users can pick any site around the world, and then the software will automatically pull the topographical, and environmental data to assess the feasibility of the user's input. Next, it will generate and compare multiple layouts to figure out the optimal configuration based on terrain, capacity, and equipment choices. RatedPower can conduct detailed topographic analysis, and thus design layouts that are adaptable to complex terrain like hills and automatically calculate the needed infrastructure which can be a substantial cost for large projects. RatedPower also has an extensive, updated database of equipment like PV modules, inverters, and mounting infrastructure. This software tool is integrated with PVsyst to output energy yield which allows for forecasts of energy production of the chosen site location.[63]

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A very similar software tool to Aurora Solar is OpenSolar which has the same features, and core functionality of Aurora Solar, except OpenSolar is completely free to use, and offers an open API. Additionally, OpenSolar supports numerous languages, and currencies which supports use across multiple regions. An important aspect to note is that OpenSolar does offer premium, paid services like expert 3D designs or permit-based design services.[64]

Another cloud-based design software platform that is primarily meant for the Australian market is Pylon. Pylon is primarily designed for the commercial and industrial sector and includes PV system design, financial modeling and proposal tools. One of its key features is the ability for the user to upload customer interval data, which allows the software to analyze electricity usage, and demand charges for the financial estimate. This makes the interval-data analysis especially useful for commercial projects where electricity rates and demand charges can be more complicated.[65]

Solo Solar is another software platform that is designed for the solar and roofing sectors and streamlines parts of the process from planning to final installation. Solo provides various tools for design which includes 2D and 3D drawings, PV system animation and real-time editing, allowing companies to make changes as they talk to the customer in real-time. Furthermore, Solo can integrate with lenders to provide loan quotes, and can automate the creation of contracts and other documents, reducing manual workflow time.[66]

Solar Nexus is another tool used by solar contractors, and was acquired by Solo Solar.[66] This software tool allows contractors to obtain, qualify, and manage leads while storing client data and site data. Solar Nexus can generate cost estimates, financial documents, and PV array designs using aerial imagery, and module databases. It can also create hourly energy-output simulations while taking load reductions, and efficiency assumptions into account.[67]

Arka360 is another software tool that is designed for the pre-sale and design stages of a solar project. Arka360 allows users to create 3D rooftop models, perform shading analysis while taking site obstructions into account, and estimate the energy output of the proposed PV system.[68]

Project Sunroof by Google is a free tool that uses Google mapping and solar-resource data to help homeowners, and businesses understand the solar potential of a rooftop, and possible electricity-cost savings. The main feature of this tool is its ability to analyze the solar potential of a chosen rooftop after the user enters an address. It can take obstructions, and shading into account, and estimate the annual solar exposure of the roof. It also combines local weather data with electricity rates to estimate possible savings over a period of time, such as 20 years. Project Sunroof allows users to view solar-potential information for larger areas such as cities, counties, states, or zip codes.[69] The main limitation is that these are preliminary estimates and not a replacement for a detailed site-specific engineering design.

As a National Lab, NLR offers numerous tools for the pre-planning stages of a PV system which include System Advisor Model (SAM), and bifacial_radiance.[70,71] SAM is a desktop software designed to provide an economical and technical analysis of renewable energy projects that include solar energy projects. SAM allows users to specify system components including specific PV modules, inverters, batteries, and other components, and then performs an hour-by-hour simulation to predict the energy output. The main feature of SAM is its ability to model a wide variety of financial structures such as residential, commercial, power purchase and many more agreements. While SAM does not use AI or ML methods, it can be utilized in a project's financial analysis, and SAM's open source API can also be integrated into other applications that are ML or AI based.[70] Bifacial_radiance is a toolkit that allows researchers to focus on bifacial solar modules. This tool takes advantage of a ray-tracing engine to model the light in a PV farm which allows researchers to understand how much sunlight is being reflected off the ground onto the back of the PV modules. Bifacial_radiance allows users to change parameters such as row spacing, module size, reflectance of the ground etc. This tool can also generate hourly and annual irradiance, and energy output data for both the front and back of the PV modules.[71] Similarly to SAM, bifacial_radiance is not AI or ML based but its output data can be used to train ML models to create less computationally expensive approximations of bifacial performance.

All of the software tools and packages stated above utilize computer vision technology to analyze sites and locations while blending in ML algorithms to optimize the layout, and equipment that is used. These algorithms will be explored more deeply later on in the paper to ensure a full understanding of the complexities that occur in these software tools.

Machine learning & artificial intelligence for forecasting and grid integration

The amount of solar energy available to a PV system can change quickly because of clouds and other weather conditions. This creates a problem for balancing supply and demand since the output of a PV system can change throughout the day. As a result, weather, irradiance, and PV power forecasting are important for grid integration and system planning. This subsection looks at the software tools, APIs, and research projects that are used for forecasting, and managing DERs.

Solcast is an application programming interface (API) tool that provides solar irradiance, and weather data catered to the solar industry. Solcast covers most of the world except the poles, and some of its data products are available at 5-minute intervals, and spatial resolutions down to 90 meters. The data includes global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), temperature, wind speed, humidity, and other atmospheric conditions. Solcast also provides historical, real-time, and forecast data, and can be used as an input for PV power modeling when characteristics like panel model, azimuth, tilt and other system parameters are provided.[72] Another similar tool is DTN, although DTN serves several industries including solar. DTN provides weather and forecast data that can also be used for solar-energy applications.[73]

Regarding grid-integration focused tools, distributed energy resource management systems (DERMS) are software tools that allow grid operators to monitor and manage distributed energy resources (DERs) like PV systems, batteries, electric vehicles, and other distributed devices. Some major commercial companies in this area include Siemens and Schneider Electric.[74,75] Siemens offers Gridscale X (Figure 20), which includes tools for grid planning, monitoring, and DER analysis.[74] Schneider Electric's EcoStruxure Grid (Figure 21) also provides monitoring, grid-management, and hosting-capacity functions for DER integration.[75] These platforms rely on meter, weather, system, and communication data, and since the software is proprietary, the exact internal algorithms are not always available publicly.

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Figure 20 Gridscale X Software Representation. Reprinted from Siemens.[74]

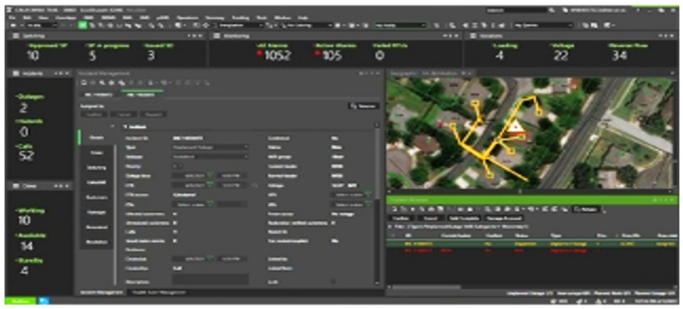

Figure 21 EcoStruxure Grid Software Representation. Reprinted from Schneider Electric.[75]

Enode io is an API tool that allows businesses and individuals to connect numerous energy devices with each other, and aims to simplify the complicated process of managing DERs. The primary function of this tool is its ability to allow users to connect a wide array of devices like electric vehicles (EVs), solar inverters, batteries, fridges etc. with a wide database of brands, and specific model types. Enode simplifies the process by obtaining data about numerous brands and models from one single API which saves time and computational power. Enode allows users to send commands back to the devices such as optimizing chargers, shifting energy consumption from peak hours, monitoring energy usage, and numerous other applications.[76]

NLR also works on several research projects for grid modeling and management. FAST-DERMS (Federated Architecture for Secure and Transactive Distributed Energy Systems) develops a structure for coordinating DERs across utilities, aggregators, and other participants. Rather than having every DER controlled by one central system, the project uses a federated structure in which utilities, aggregators and other authorized groups can manage different DERs while still participating in grid services. It also looks at voltage, frequency, supply and demand, and cybersecurity.[77] Another NLR project is Reorg, which studies how a larger distribution grid can be separated into smaller cells or microgrids that can coordinate with each other, and be isolated when needed during a disturbance.[78]

NLR also has projects focused on forecasting. One example is probabilistic cloud day-ahead forecasting, which gives a range of possible outcomes, and their probabilities instead of only one forecast value. The system uses ensembles of numerical weather prediction (NWP) models with different starting conditions to account for uncertainty.[79] Another project focuses on probabilistic net-load forecasting using deep learning methods. This is useful in areas with large amounts of behind-the-meter solar because the solar generation changes the net load seen by the utility. The project was tested using real utility data, including data from Hawaiian Electric.[80]

Machine learning & artificial intelligence for maintenance and damage repair

So far, this paper has analyzed various ML tools, and software available to optimize PV system efficiency and output. However, like any technology, regular upkeep is important to ensure long-term operational capabilities. Before the advent of ML, the solar industry was focused on reacting to faults, and problems after they had already happened, and maintenance was generally not frequent but rather was monthly, or sometimes annually depending on the situation. However, with the emergence of ML, the solar industry is shifting to a more proactive based maintenance schedule that also prioritizes preventing the problem before it can occur which maximizes the time a PV system is kept operational.

Before diving deeper into the various tools, and packages available on the market, it is important to understand some of the major faults and problems that can occur in a PV system/plant. Firstly, there are 3 different types of faults in PV systems, these are incipient, abrupt, and intermittent faults.[3,81]. Incipient faults can begin with relatively small changes and may be more difficult to detect than abrupt faults.[3] Abrupt faults occur rapidly, and can include line-to-line faults (short circuit between two lines in a PV array) or line-to-ground short circuits (point of the array and ground).[3]. Intermittent faults appear and disappear over time, and some examples can be associated with varying operating or environmental conditions.[3,81] Furthermore, short-circuit and abnormal-operating conditions can include hot spots, open-circuit conditions, and arc faults.[3] Hot spots (Figure 22) can be associated with partial or complete shading, soiling, defects, or mismatch that increases the temperature of a local cell or module region. Open-circuit faults can occur when an electrical path is disconnected in a PV array. Arc faults (Figure 23) can result from loose, damaged, or degraded electrical connections and insulation.[3,81]

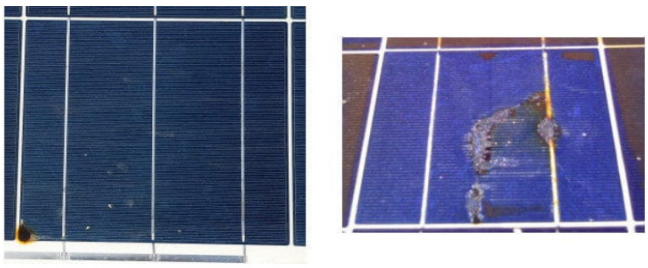

Figure 22 An Image of a Hot Spot Fault. Reprinted from Andrews R, et al.[82]

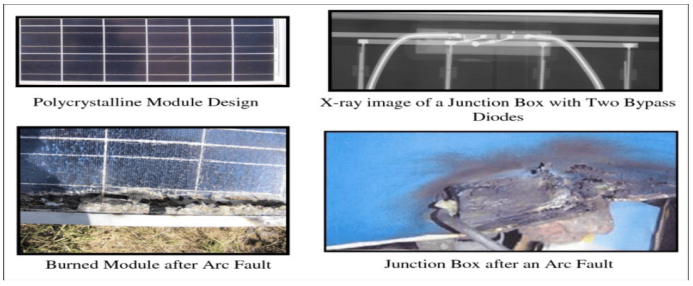

Figure 23 Several Images of an Arc Fault. Reprinted from Johnson J, et al.[83]

One form of PV inspection involves using drones with thermal and RGB cameras to capture high-resolution images of a PV plant for analysis. Some commercial tools in this area include Raptor Maps

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(Figure 24), and SenseHawk.[84-86]. Raptor Maps focuses on solar inspections, digital mapping, and performance management, and can connect thermal and RGB imagery to mapped PV assets to help identify, and document anomalies.[84,85] SenseHawk also uses aerial imagery but is focused more broadly on construction, inspection, and operations.[86] These image-based inspections are useful for visible, and thermal abnormalities, but they do not replace all forms of electrical testing, and the results can depend on image quality, weather, and operating conditions.

Figure 24 A RaptorMaps Drone Inspecting a PV Power Plant. Reprinted from Raptor Maps.[84]

PowerTrack by AlsoEnergy is a cloud-based software platform for real-time monitoring of PV system performance. It can collect data from on-site hardware like sensors, meters, and inverters. For large-scale projects, it also includes supervisory control, and data acquisition (SCADA) functions that allow remote monitoring, and control. The platform also uses analytics, and alarms to help operators identify, and prioritize problems with the system.[87]

Fracsun is another company that focuses more specifically on PV soiling measurement, and modeling, which is especially relevant in dry, dusty, and agricultural regions. Fracsun's CLEO AI tool models the energy losses caused by soiling, and helps operators compare cleaning schedules; it does not physically remove the soiling itself. The company also uses on-site soiling monitoring stations (ARES), weather data, and atmospheric information as inputs. This data is then used to estimate how soiling changes over time, and how it can affect energy production.[88]

Behind the scenes of ML/AI based software tools and packages

The above subsections have analyzed the various types of software tools and packages that are available on the market right now for PV system optimization and management. However, the main algorithms and specific techniques, and how they work were not previously mentioned in detail. Thus, this section explains several ML techniques and methods that have been applied to PV forecasting, optimization, inspection, and control.

Before diving into the core of the specific ML techniques, it is important to distinguish between algorithms documented in the PV research literature and the internal methods used by proprietary commercial software, which are not always publicly disclosed. Across the PV literature, CNNs have been applied to image-based inspection and defect detection; genetic algorithms (GA) and particle swarm optimization (PSO) to optimization problems; LSTMs, GRUs, and other neural-network methods to forecasting; and reinforcement learning (RL) and multi-agent systems (MAS) to control and grid-related problems.[3,81] Therefore, the following discussion focuses on these documented algorithm families rather than assigning a specific internal architecture to every commercial platform. Figure 25 shows a tree diagram of some of the ML algorithms mentioned above. The AI/ML equations used in the solar industry are summarized in Table 3. The common ML methods utilized in the solar industry, by PV application, is summarized in Table 4.

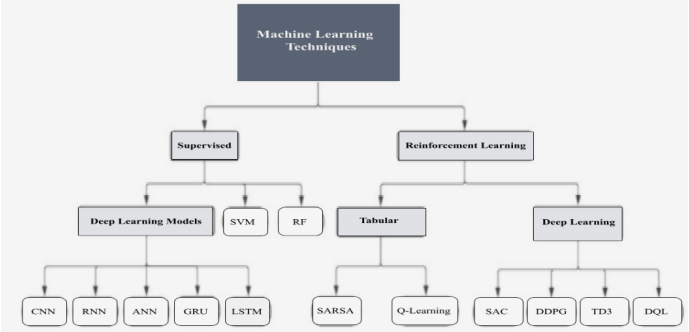

Figure 25 A Tree Diagram Showing ML Techniques. Adapted from Gaviria JF, et al.[3]

Table 3 AI/ML Equations Used in the Solar Industry.

Methods and architectures	Brief description	PV application examples
Artificial Neural Networks (ANNs)	Models inspired by the human brain that detect patterns for prediction and classification	Used to forecast solar irradiance data and optimize power output
Convolutional Neural Networks (CNNs)	Models that process grid-like data using layers called convolutional layers to learn spatial features	Used in drone inspections of PV systems to detect and classify faults like hotspots or cracks
Long Short-Term Memory (LSTM) & Gated Recurrent Units (GRUs)	Advanced types of Recurrent Neural Networks (RNNs) for time-series forecasting that use gates to identify long-term dependencies	Used to predict solar irradiance via learning patterns from historical weather reports
Random Forests (RFs)	A group of decision trees that average predictions to counteract overfitting of data	Used in PV systems to predict overall performance and identify the features that influence performance the most
Gradient Boosting	Similar to RFs, but builds models (usually decision trees) in a sequential manner to correct previous errors using gradient descent to reduce loss	Used to create accurate models to predict the performance of a PV system
Support Vector Machines (SVMs)	A supervised algorithm that finds the optimal hyperplanes to separate data for classification and regression	Used mainly for fault detection in PV systems like diode failure, cracks, and much more
K-Nearest Neighbors (KNNs)	A simple algorithm that predicts based on the "k" closest data points for classification and regression	Used to detect PV module soiling from historical conditions

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Table 3 Continued..

Genetic Algorithms (GAs)	An evolution-inspired search heuristic algorithm that iteratively evolves solutions using selection, crossover, and mutation	Used to optimize PV system layouts and performance
Particle Swarm Optimization (PSO)	A swarm-inspired optimization algorithm where particles adjust their positions based on individual and group bests	Used to optimize PV system variables and parameters like the size of the array or battery configuration
Reinforcement Learning (RL)	A trial-and-error learning method where agents take actions to maximize rewards while minimizing penalties	Used in MPPT to counteract complex PV power-voltage curves and find the true MPPT
Multi-Agent Systems (MAS)	Multiple agents that interact with one another and learn policies while considering the actions of other agents	Used for advanced, cooperative microgrid control of PV systems

Table 4 Common ML Methods Utilized in the Solar Industry by PV Application.

Application	Common ML methods	Typical use	Example focus
Forecasting	LSTM, GRU, RF, SVM	Time-series prediction	Irradiance, PV Output, net load
Fault detection	CNN, classification, anomaly detection	Image or signal analysis	Module defects, hot spots, faults
MPPT / optimization	RL, Q-learning, PSO, GA	Control and search	Maximum power point, layout optimization
Grid control	RL, MAS, forecasting models	Decision-making and coordination	DER management, grid support

Results & Discussion

The rapid introduction and integration of ML and AI powered software tools in the solar industry has created a large number of platforms for different parts of a PV project. Due to this, it can be difficult for individuals and businesses to identify which tool actually fits the task they are trying to complete. The capabilities, assumptions, limitations, costs, and accessibility of these tools can also vary greatly. Consequently, this section compares the software tools described in Section 3 using the same general guideline. This includes the tool's profile, main capabilities, assumptions or required inputs, limitations, and licensing/accessibility (Figure 26). Since all of the tools were not tested on the same dataset or under the same conditions, the comparison is descriptive rather than a direct one company against another benchmark.

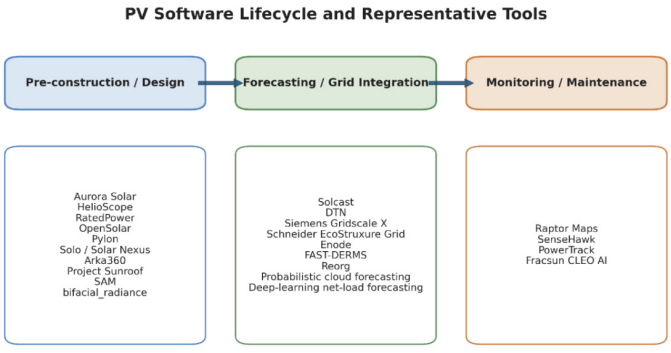

Figure 26 PV software lifecycle and representative tools analyzed in this review.

Comparison of pre-construction and optimization platforms

Aurora Solar is a United States (US) based company that serves the residential, and commercial market, while HelioScope, which was acquired by Aurora Solar, is tailored more toward commercial, and industrial markets. Both software tools can create 3D site models from aerial, and LiDAR data, and offer shading analysis, financial analysis, reports, and energy-yield estimates. Aurora Solar is more focused on connecting design with the sales, and project workflow, while HelioScope is more focused on detailed engineering, and design. Both tools depend on the quality of the imagery, weather data, component specifications, and other inputs given by the user. One limitation is that unusual sites, custom equipment, or newer components may not be represented as well if the needed information is not available in the software's database. Both are proprietary platforms.[59-62]

RatedPower, located in Spain, focuses on large-scale, utility PV farms. Its major strengths include generating and comparing multiple PV farm layouts based on the chosen area's topography, equipment, and project constraints. This layout design can also include civil engineering planning like Earthworks, and the platform can integrate with PVsyst for energy-output reports. RatedPower assumes access to accurate topographical, environmental and equipment data for the chosen site. One of its main limitations is that it is not as well suited for smaller residential projects, and is more focused on engineering and plant design than sales or customer proposals.[63]

OpenSolar is another software tool that is headquartered in Australia while maintaining some offices in the United States. OpenSolar has numerous features like 3D design, shading analysis, energy-output simulations, permit support, and an open API that allows

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it to be integrated with other tools and projects. One limitation for this comparison is that the sources reviewed contain more information from OpenSolar itself than independent head-to-head testing against engineering benchmarks. However, the free core platform, and open API make it accessible for smaller projects, and users that do not need a paid engineering platform.[64]

Pylon is a tool that is primarily focused on the Australian commercial, and industrial solar market. One of its key features is the ability for the user to upload interval electricity data for analysis. This allows the software to include electricity usage, and demand charges in the financial estimate, which is especially useful for commercial projects where electricity costs can be more complicated. One of its main limitations is its geographic focus, and its design features are less extensive than some of the larger engineering platforms discussed above.[65]

Solo and Solar Nexus, which was acquired by Solo, are companies based in the US, and are software applications that focus on streamlining workflow primarily for residential projects. Both tools include design integration, customer relationship management (CRM), proposal tools, and contract automation. Their main limitation is that they focus more on sales, workflow and project management than deep engineering analysis and detailed optimization of the PV layout.[66,67]

Arka360 is another software company based in the US focused on the pre-sale and design stages of solar projects. Its features include 3D rooftop modeling, shading analysis, energy-output estimates and proposal tools. One of its limitations is that it is more focused on design, and proposal work than managing the full lifetime of a solar project.[68]

Project Sunroof by Google is more of an awareness and general information tool rather than a complete platform for PV system design. It uses mapping, roof, and solar-resource information to estimate the solar potential of a home or area, and possible electricity-cost savings. One of its main limitations is that it provides a rough, preliminary estimate and cannot account for every site-specific detail, equipment choice, or engineering requirement. Project Sunroof is free to use where coverage is available.[69]

Next, there are two projects by the NLR called SAM, and bifacial_radiance. SAM is not an AI based tool but is a physics based simulator that can be integrated with other tools that use AI or ML methods. SAM's major strength is its ability to perform detailed, hour-by-hour performance, and financial analysis for solar projects with a wide variety of options for financial structures. SAM assumes that the user has enough technical knowledge to configure the large number of parameters correctly. One of its main limitations is the learning curve, and the fact that it is not designed as an automated sales or layout-optimization platform. However, SAM is free, and open source which makes it useful for research, model development, and other applications. Bifacial_radiance is also not an AI or ML tool but is a ray-tracing physics engine that models light interactions such as ground reflections in bifacial solar plants. This tool assumes the user has experience with programming and optical modeling since it is a Python-based toolkit. Its main limitation is that it focuses on a specific modeling problem instead of the full PV project workflow. Similar to SAM, bifacial_radiance is free and open source.[70,71] A block diagram of software tools for pre-design and optimization is presented in Figure 27.

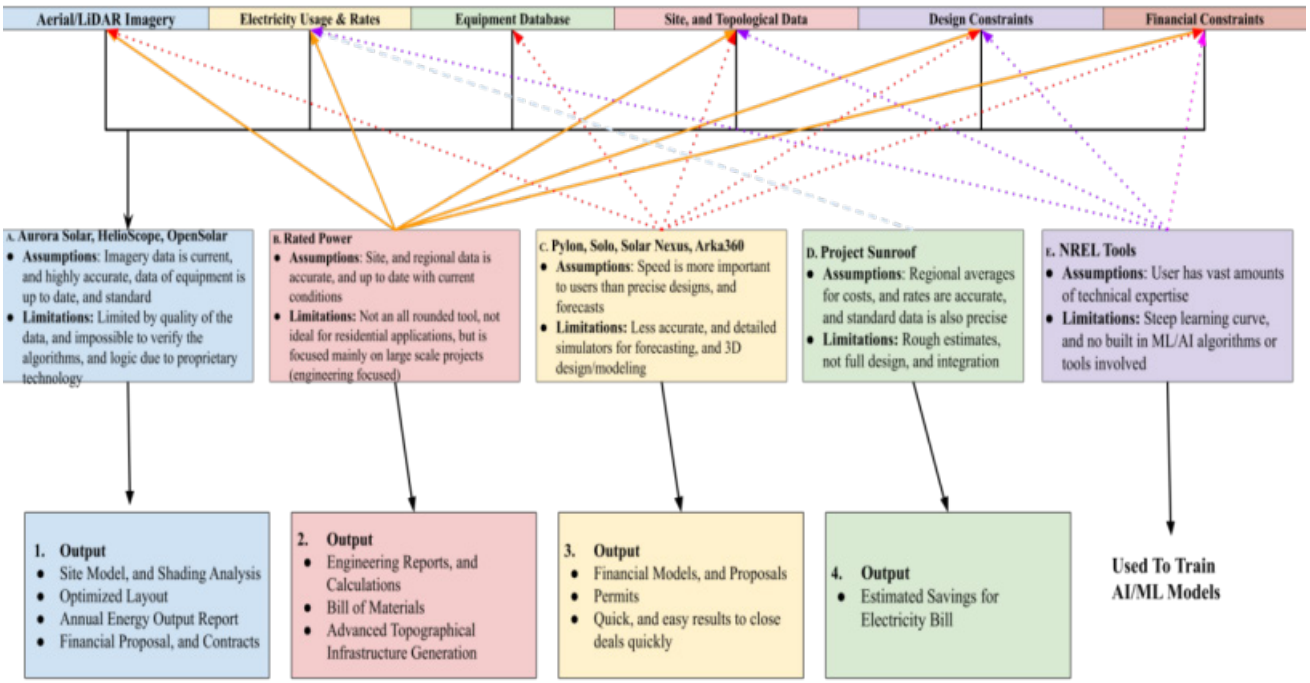

Figure 27 A block diagram of software tools for pre-design and optimization.

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Comparison of forecasting and grid integration platforms

Solcast is a company based in Australia that is focused primarily on the solar industry, while DTN is a US-based meteorological analytics firm that serves several sectors. Both tools offer weather and solar-resource data through APIs. However, Solcast is more specifically focused on solar irradiance and PV modeling while DTN is broader. One limitation of both services is that forecast accuracy generally decreases as the forecast horizon becomes longer. In addition to this, the internal details of the proprietary forecasting systems are not always available to the user. Solcast also offers some free data, and research access.[72,73]

Siemens, the German company, and Schneider Electric, a French company, provide enterprise-scale DERMS and grid-management systems. Siemens offers Gridscale X, while Schneider Electric offers EcoStruxure Grid. Both platforms include monitoring, forecasting, coordination and control functions for distributed energy resources. These systems depend on the grid having the proper sensors, communications, control infrastructure and cybersecurity in place. One of their main limitations is the complexity involved in integrating a large utility-scale system, and the requirements can vary greatly from one grid to another.[74,75]

Enode is an API company based in Norway that focuses on connectivity between energy devices. Enode acts as a common API layer that allows outside applications to connect to, and control devices from multiple brands. One of its main limitations is that Enode does not perform all of the forecasting or optimization by itself; instead, it mainly acts as the connection layer between the application and the devices.[76]

Some foundational research projects from NLR include FAST-DERMS, The Reorg Project, and advanced forecasting models like probabilistic cloud forecasting, and deep-learning-net-load forecasting. FAST-DERMS allows for secure access across multiple areas like utilities, aggregators, etc. The Reorg Project utilizes a novel concept of reorganizing the larger grid into smaller, automatic microgrids which allows for cooperation across various parts of the grid, and much stronger resilience against outages. Both of these projects assume a grid that has numerous DERs where centralized control is not ideal for efficient operation. However, both of these projects are still in the research stage, and are not available on the market but are just frameworks. Both of these projects' designs, findings, and code are open-source, and free intended for the greater public benefit.[77,78]

Probabilistic cloud forecasting is another NLR research project used for solar forecasting, and it provides a range of possible outcomes instead of only one forecast value. In addition to this, deep-learning net-load forecasting uses data-driven methods to predict net load. Both are research tools rather than ready-to-use commercial software, and they can require technical expertise and significant computational resources to run. Since they are public research projects, the reports, methods, and other research outputs are available through the associated project resources.[79, 80] Figure 28 presents a block diagram of software tools for forecasting and grid integration.

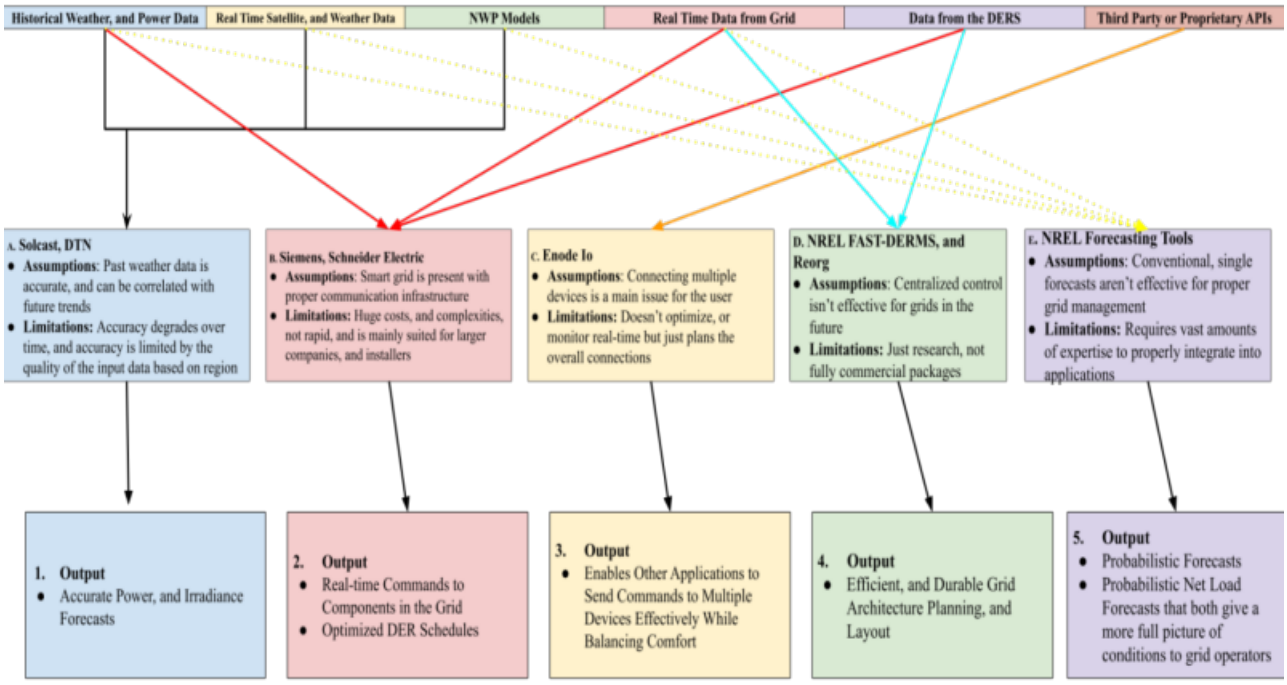

Figure 28 A block diagram of software tools for forecasting and grid integration.

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Comparison of maintenance and damage repair platforms

Raptor Maps, and SenseHawk are US-based companies that use drone and aerial imagery to inspect PV plants. Raptor Maps is more focused on creating a digital representation of the PV plant for inspection, mapping, and performance management, while SenseHawk covers a broader part of construction, inspection, and operations. Both tools depend on usable aerial or thermal imagery, and weather or flight conditions can affect the inspection. Another limitation is that image-based inspection is mainly useful for visible and thermal abnormalities and does not replace all forms of electrical testing.[84-86]

AlsoEnergy, and Fracsun are both US-based companies that focus on site monitoring, although Fracsun is more specialized. The PowerTrack platform by AlsoEnergy is focused on real-time SCADA monitoring and alarm functions, while Fracsun's CLEO AI focuses specifically on modeling the energy losses caused by soiling. PowerTrack depends on accurate data from the on-site hardware, while Fracsun depends on local soiling, weather, and atmospheric data being representative of the site. One limitation of CLEO AI is that it is focused on soiling rather than general PV faults, while PowerTrack covers a wider range of monitoring functions but still depends on the quality of the connected sensors and site data.[87,88] A block diagram of software tools for maintenance and damage repair is presented in Figure 29.

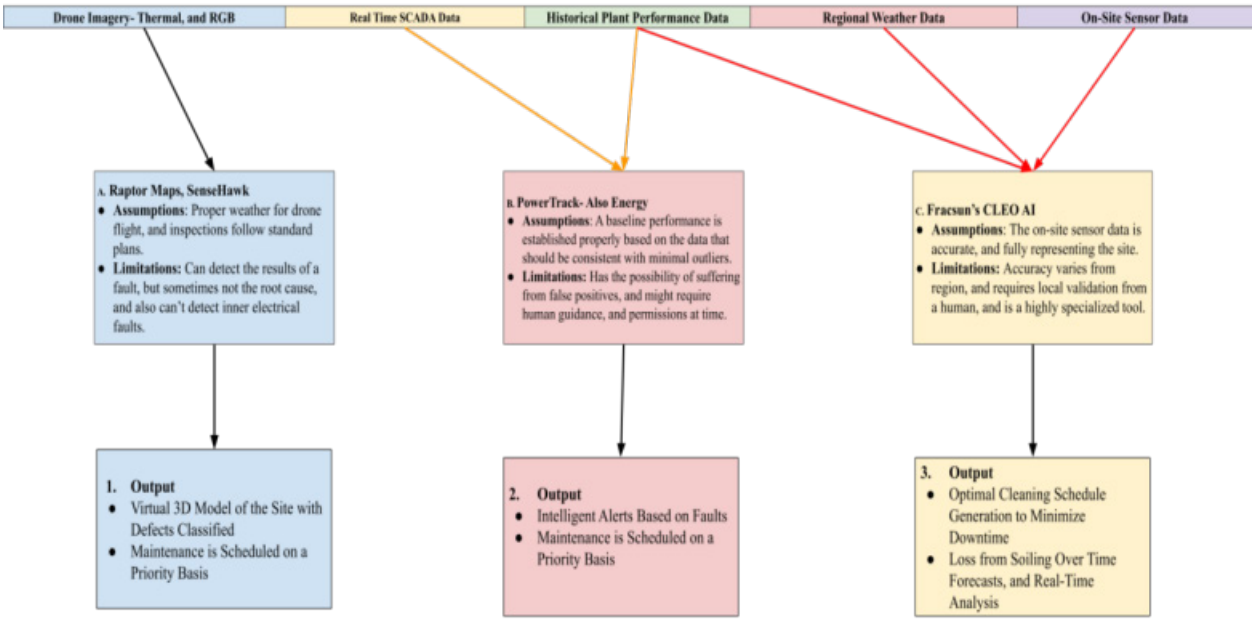

Figure 29 A block diagram of software tools for maintenance and damage repair.

Note: The above software tools are all of the same ones mentioned in section III with the same references.

Conclusion

AI and ML techniques have transitioned from primarily academic and research concepts into tools that are now being used throughout different parts of the solar industry. The software tools and packages, reviewed in this paper, serve a variety of purposes including system design, forecasting, grid integration, monitoring, maintenance, and research. However, these tools were not all created to solve the same problems, and they differ in areas such as their capabilities, assumptions, limitations, costs, and accessibility. Because of this, directly comparing every software platform under one standard would not be completely appropriate unless they were tested using the same conditions, data and evaluation methods. Therefore, this paper focuses more on what each tool is designed to do, along with its strengths, limitations, and possible use cases. There is also no single software platform that can be considered the best for every PV application. All-in-one sales, and design platforms such as Aurora Solar focus heavily on combining design with other parts of the project workflow, while utility-scale tools such as RatedPower are more focused on engineering and plant design. Services such as Solcast are centered around forecasting data, platforms such as Raptor Maps are focused more on inspections and asset information, and NLR tools are generally more useful for research-oriented modeling. These differences show that the usefulness of a platform depends greatly on what the user is actually trying to accomplish. Since the software tools discussed in this review were not independently tested against each other using the same dataset, conditions, and evaluation criteria, this paper does not determine that one platform, or combination of platforms, is better than all of the others.

There are also limitations that appear throughout several of the software tools discussed in this paper. For proprietary platforms, many of the exact models, algorithms, and internal methods are not always publicly available, making it difficult to fully understand how some outputs are being produced. In addition to this, the results produced by these tools can depend greatly on the quality, amount, and accuracy

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of the data being used. Future work could compare these platforms using the same datasets, conditions, and evaluation methods, while also looking further into how different tools can work together and how well they perform using real PV system data. RL-based methods and other developing AI techniques could also be explored further for PV monitoring, optimization, and control, but more testing would be needed before they can be used reliably in larger real-world systems. Continued research in both PV hardware and software will be important for determining where these technologies can provide meaningful improvements, and where their limitations still remain.

Lastly, there is a crucial need to explore and to experiment with unconventional designs, and tweak the physical properties of existing types of PV module technology or try to develop new ones that are affordable, but efficient. While AI and ML tools offer powerful solutions that can contribute towards a cleaner and more sustainable future, it is up to us to select, analyze, test, and calibrate these models by applying them in the real world to determine the true capabilities of these models.

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