Smart systems and algorithms for photovoltaic arrays management

ELEC5032M Modern Industry Practise

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Abstract

The scope of this essay is to discuss and analyse specific aspects that concern renewable sources of energy and specifically photovoltaics from the perspective of what methods and systems are vital in order to create a smart system that can be used to fully exploit their potential. These methods include power forecasting algorithms, solar irradiation forecasting algorithms and finally how all these are integrated on a smart grid that can be used to distribute the produced energy. This essay will analyse briefly the process of power forecasting on photovoltaic arrays as well as the solar irradiation forecasting method. For both methods parametric and stochastic models will be discussed and how these models are utilized to perform predictions. A brief reference on the mechanism of degradation is provided, what are the possible factors that cause it. Finally, the concept of smart grid integration will be discussed as well as certain aspects of it such as, demand response, smart control etc. A conclusion is drawn at the end.

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Introduction to photovoltaics

The fabrication of photovoltaics starts at a fab plant as a giant seed of silicon. The seed is melted into giant moulds or tanks and then two methods are applied, forming crystal photovoltaics. Initially, the Czochralski method forms monocrystal photovoltaics and it produces high efficiency cells. The produced solar cells are called monocrystal since they are made up of a single crystal of silicon (homogeneous silicon lattice) [1]. Secondly, the float zone method produces polycrystal solar cells which have a homogenous atomic structure at only specific regions of the whole lattice. This method differs from the previous one at the point where the melted silicon is utilized to form the cell. During the Czochralski method, the melted silicon is pulled upwards while doping it with phosphorus or boron, while during the float zone method the melted silicon is inserted into giant moulds and injected with impurities. Both of the seeds are sliced to form the cells. Other technologies used in photovoltaic industry are the amorphous silicon, PERL and PERC cells. All these cells essentially exploit the properties of reflection and absorption of the texture of specific materials to fulfil their purpose. [1]

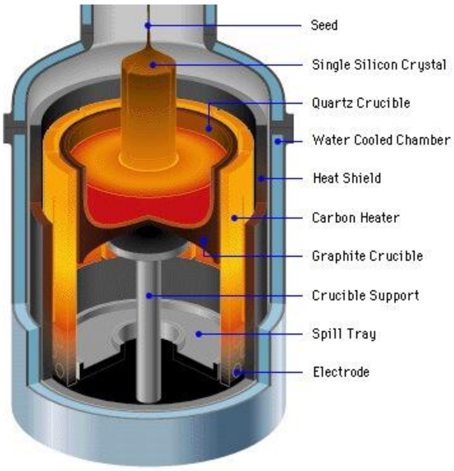

Figure 1 Czochralski method [17]

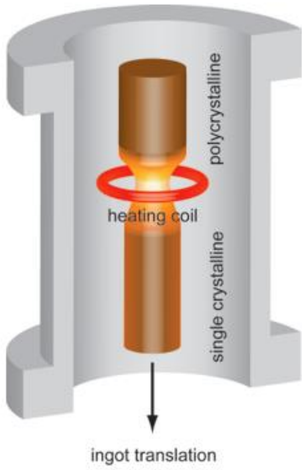

Figure 2 Float zone method [18]

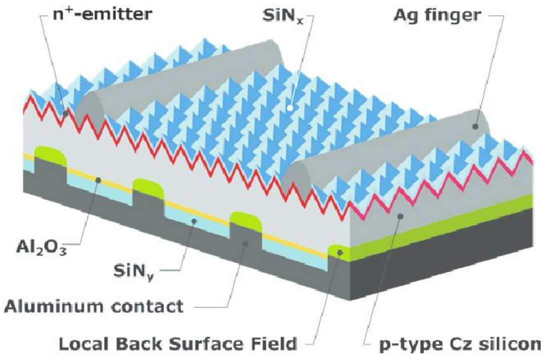

Figure 3 Perl Cell [19]

[2]

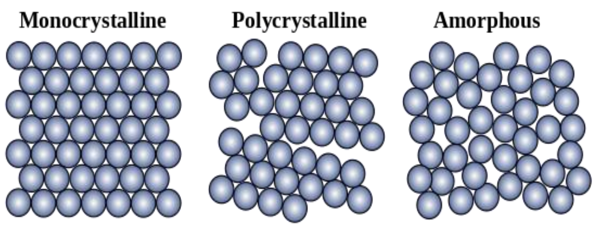

Figure 4 Form of the various photovoltaic cells [20]

Power forecasting of photovoltaic arrays

A photovoltaic array is a collection of modules. These modules consist of solar cells which function by having as underlying principle the photoelectric/photovoltaic phenomenon effect. Solar PV cells produce power which is directly proportional to the direct solar irradiance that hits cell's surface [1]. At the same time the efficiency of the cell increases as the temperature decreases. As more photons hit the surface more energy is delivered to the carriers in the various energy bands, resulting at letting them move on the silicon lattice. The fact that silicon is doped with boron or phosphorus enlarges the number of free carriers [1]. In combination with low cell temperature the effect of recombination is minimized resulting at higher population of free carriers and thus higher output current from the cell. There are a lot of parametric models for PV power forecasting which embed parasitic resistances and coefficients that are dependent on the material of the cell [1][3]. These models usually include an equivalent circuit of the cell and the output current and voltage are used to define the produced power [3] [1]. The parameters of the temperature and solar irradiance are included in the equations. Although the parametric models provide accuracy at certain cases, they require to fully analyse a cell before attempting to extract the equation. An alternative way of building power production models is the artificial intelligence method. Using machine learning methods, power production models can be built easily having only a dataset containing time, ambient temperature, solar irradiation or other numerical weather parameters [4]. An efficient architecture is the Bayesian regularization neural networks. These networks have the ability to cancel out any neurons that are redundant for the final calculation. Since machine learning models have high generalization properties can cope with different co-existing technologies on a smart grid [1] [4].

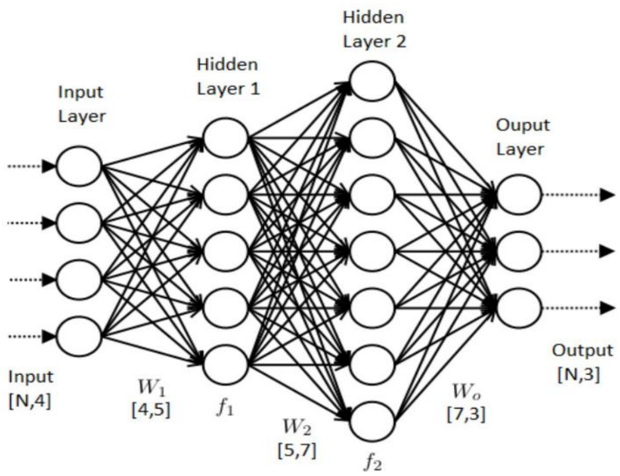

Figure 5 Feedforward artificial neural network architecture [2]

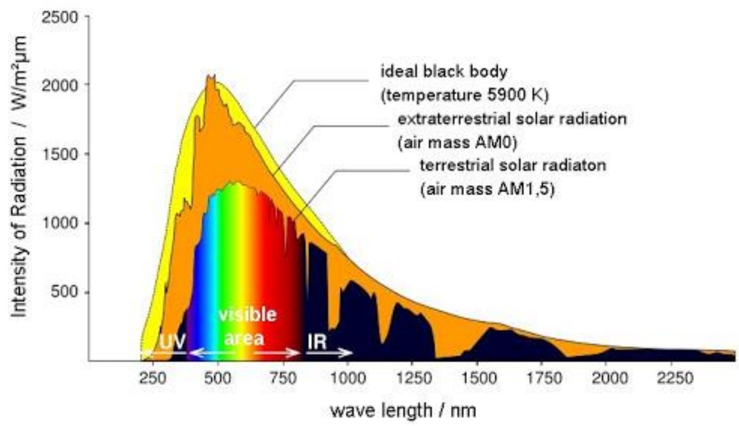

Figure 6 Light spectrum of solar irradiation [21] [22]

Solar irradiation forecasting for photovoltaic arrays

A vital aspect on the forecasting of power produced by PVs is the solar irradiation forecasting. Since the demand on a smart grid is always variable is important to execute regular forecasts that will enable the network to work smoothly and manipulate the power generation of all of its sources [5] [1]. PVs are directly dependable from solar energy, therefore an accurate power forecasting requires good solar irradiation forecasting. The most usual way to execute this type of forecast includes the use of a Neural Network [6]. The dataset used for training includes numerical weather parameters like azimuth angles of a pyranometer and sky index. These define how the sun rise time, set time and irradiation reaches earth at a certain time interval on a specific longitude and latitude on the planet. The sky index is usually defined as the ratio between the extra-terrestrial irradiation and the incident irradiation reaching to earth [7]. Some novelty on this field makes use of sky images, using a sky camera, to define with accuracy the sky index locally [8]. The cloud cover is defined by comparing the ratios between red, green and blue elements of the images' pixels [1] [9]. The images are used for training using a convolutional neural network in order to minimize the information from the image and then extract the most significant features. These features are then feed to a feedforward neural network which uses the extracted features of the image and the numerical weather parameters to construct a fitting model [6] [7] [10]. This model can then forecast the clusters concerning the sky index. Models for each cluster can be individually developed. The sky index can be fully described by 10 clusters ranging from a fully clear sky (cluster 1) to a fully cloudy sky (cluster 10) [1] [8].

Figure 7 Sky imager used for intraday solar irradiation forecasting [22]

Figure 8 Sky image from the imager [22] [11]

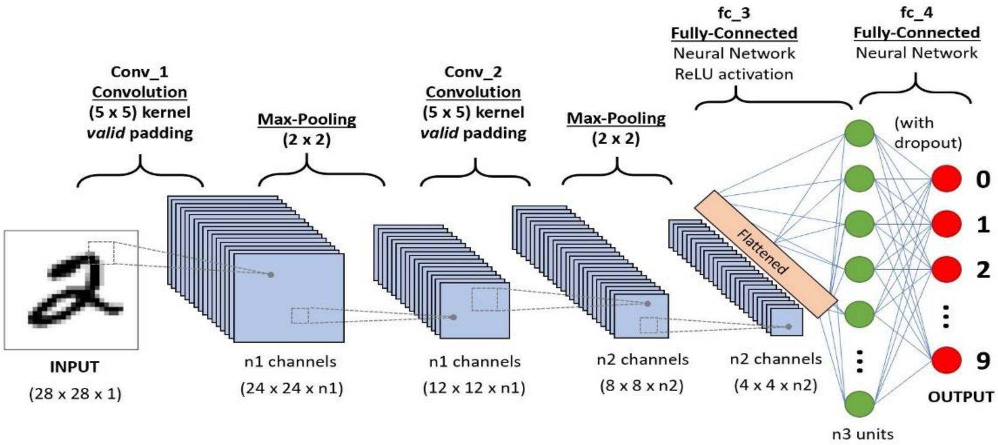

Figure 9 Convolutional neural network [11]

Smart grid integration

The above algorithms are embedded to a smart grid where the photovoltaics are connected. Each PV system acts as an independent source of power generation, therefore knowing the exact amount of power that will be produced at a future time is vital for adjusting the demand response and thus better manipulating net metering [3] [1]. The advantage of such a grid is that every owner who has a PV system can be a producer and consumer simultaneously. During peak hours the excess energy from PVs can be fuel the network of users and fulfil the demand for power. At the same time each PV system can act as independent entity and be self-preserved concerning power consumption needs. Using neural networks, the demand response can be forecasted, and the power production and distribution can be adjusted accordingly [12] [1]. All these algorithms can be implemented on embedded processors or FPGA boards. Where possible, solar trackers can be used to maximize the power production (PV modules following direct sunlight). A central server is used to host all the subsystems and coordinate all the functions, including the net metering process. Lastly, the effect of degradation is also taken into consideration as it reduces the efficiency of the cells [5] [1]. Algorithms that monitor the current produced by the cell can identify potential induced degradation and inform the owner in order to take precautions. Degradation can be caused by humidity freeze and UV exposure light, which causes corrosion on the cells [13] [14] [1].

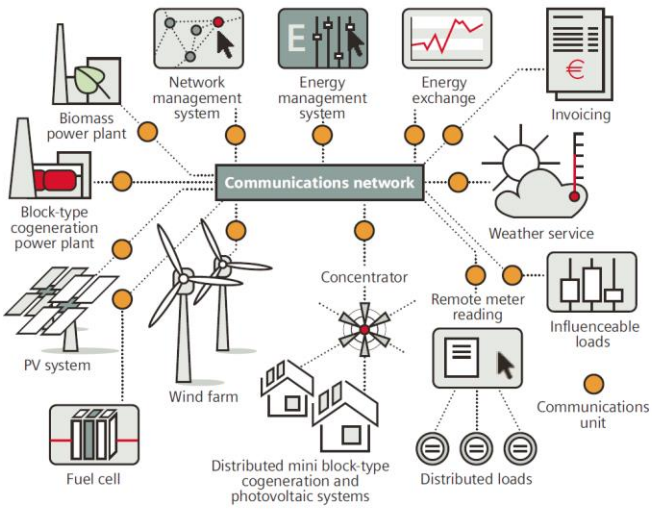

Figure 10 Subsystems connected to a smart grid [23]

Conclusions

Photovoltaic technology has evolved rapidly the last 50 years resulting at high efficiency solar cells at a viable price. The advancements in machine learning and computing have enabled the implementation of control systems and thus contributed to the development of the smart grids. Forecasting methods are vital to ensure the smooth operation of the grid, as solar cells are highly dependable from the sunlight. A variety of models have been developed including, Bayesian regularization neural networks, feedforward neural networks and parametric models including numerical weather parameters (azimuth and elevation angles, relative humidity, etc). Those can be used to monitor a system's behaviour and control the various inverters, controllers, converters and other piece of hardware vital for the functionality of the grid. In a nutshell, as science and technology advance the intelligence of such networks will be increased resulting at making them fully autonomous concerning decisions.

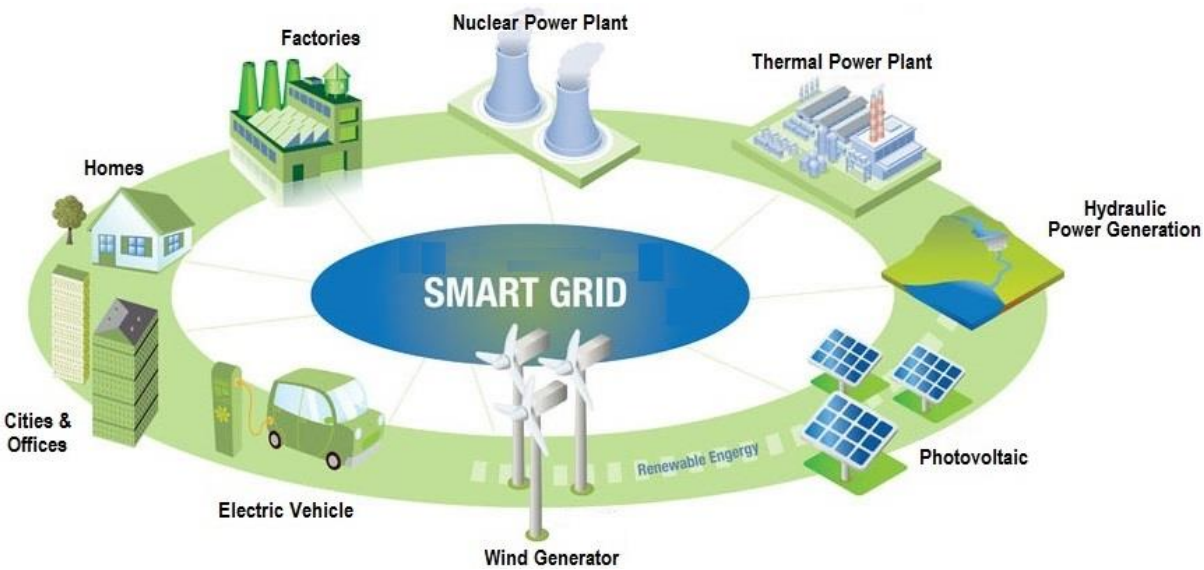

Figure 11 Smart grid embedding multiple sources of power generation [15]

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