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Towards Utilization of Machine Learning in Photovoltaics to Achieve Smarter and Cleaner Energy Generation Systems: A Comprehensive Review

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Corresponding Author:	Mohammad Hossein Doranehgard University of Alberta Edmonton, AB CANADA
First Author:	Ali Sohani
Order of Authors:	Ali Sohani
	Hoseyn Sayyaadi, PhD
	Cristina Cornaro, PhD
	Mohammad Hassan Shahverdian, PhD
	Marco Pierro, PhD
	David Moser, PhD
	Nader Karimi, PhD
	Larry K.B. Li, PhD
	Mohammad Hossein Doranehgard
Abstract:	Photovoltaic (PV) technologies are expected to play an increasingly important role in future energy production. Meanwhile, machine learning is becoming increasingly widespread owing to a confluence of factors such as advancements in computational hardware, data collection and storage, and data-driven algorithms. With this backdrop, we provide a comprehensive review of machine learning techniques applied to PV systems. First, conventional methods for modeling PV systems are introduced from both electrical and thermal perspectives. Then, the application of machine learning to analyses of PV systems is discussed. Focus is placed on reviewing the use of machine learning algorithms for performance prediction and fault detection of PV technologies, and on explaining how machine learning could help to achieve a cleaner environment in the push towards carbon neutrality around the world. This review also discusses the challenges and future perspectives of using machine learning to analyze PV systems. A key conclusion is that the use of machine learning for the analysis of PV systems is still in its infancy, with many small-scale PV technologies, such as building integrated photovoltaic thermal systems (BIPV/T), still yet to benefit significantly in terms of system efficiency and economic viability. The wider application of machine learning in PV systems could therefore create a more direct path towards cleaner, more sustainable energy production.
Suggested Reviewers:	Hafiz Ali, PhD Associate Professor, King Fahd University of Petroleum & Minerals hafiz.ali@kfupm.edu.sa
	Mostafa Safdari Shadloo, PhD Associate Professor, Normandy University mostafa.safdari-shadloo@insa-rouen.fr
	Saman Rashidi, PhD Associate Professor, Semnan University samanrashidi@semnan.ac.ir
	Fatih Selimefendigil, PhD Manisa Celal Bayar University

	fatih.selimefendigil@cbu.edu.tr
	Mohammad Reza Safaei, PhD Associate Professor, Florida International University msafaei@fiu.edu

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Ali Sohani [a], Hoseyn Sayyaadi [b], Cristina Cornaro [a], Mohammad Hassan Shahverdian [b], Marco Pierro [c], David Moser [c], Nader Karimi [d,e], Larry K.B. Li[f], Mohammad Hossein Doranehgard [f,g1]

[a] Department of Enterprise Engineering, University of Rome Tor Vergata, Rome, Italy

[b] Lab of Optimization of Thermal Systems' Installations, Faculty of Mechanical Engineering-Energy Division, K.N. Toosi University of Technology, P.O. Box: 19395-1999, No. 15-19, Pardis St., Mollasadra Ave., Vanak Sq., Tehran 1999 143344, Iran

[c] EURAC Research, Viale Druso, 1, 39100, Bolzano, Italy

[d] School of Engineering and Materials Science, Queen Mary University of London, London E1 4NS, United Kingdom

[r] James Watt School of Engineering, University of Glasgow, Glasgow G12 8QQ, United Kingdom

[f] Department of Mechanical and Aerospace Engineering, The Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong

[g] Department of Civil and Environmental Engineering, School of Mining and Petroleum Engineering, University of Alberta, Edmonton, Alberta T6G 1H9, Canada

[1] Corresponding author; Email address: doranehg@ualberta.ca (M.H. Doranehgard).

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[r] James Watt School of Engineering, University of Glasgow, Glasgow G12 8QQ, United Kingdom

[f] Department of Mechanical and Aerospace Engineering, The Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong

[g] Department of Civil and Environmental Engineering, School of Mining and Petroleum Engineering, University of Alberta, Edmonton, Alberta T6G 1H9, Canada

Abstract

Photovoltaic (PV) technologies are expected to play an increasingly important role in future energy production. Meanwhile, machine learning is becoming increasingly widespread owing to a confluence of factors such as advancements in computational hardware, data collection and storage, and data-driven algorithms. With this backdrop, we provide a comprehensive review of machine learning techniques applied to PV systems. First, conventional methods for modeling PV systems are introduced from both electrical and thermal perspectives. Then, the application

[1] Corresponding author; Email address: doranehg@ualberta.ca (M.H. Doranehgard).

of machine learning to analyses of PV systems is discussed. Focus is placed on reviewing the use of machine learning algorithms for performance prediction and fault detection of PV technologies, and on explaining how machine learning could help to achieve a cleaner environment in the push towards carbon neutrality around the world. This review also discusses the challenges and future perspectives of using machine learning to analyze PV systems. A key conclusion is that the use of machine learning for the analysis of PV systems is still in its infancy, with many small-scale PV technologies, such as building integrated photovoltaic thermal systems (BIPV/T), still yet to benefit significantly in terms of system efficiency and economic viability. The wider application of machine learning in PV systems could therefore create a more direct path towards cleaner, more sustainable energy production.

Keywords: *Machine learning; Fault detection; Accurate performance prediction; Cleaner aspect; Smart energy production;*

Nomenclature

Symbols	
A	Area (m^2)
G	Irradiance ($W.m^{-2}$)
I_o	Diode saturation current (A)
I_{ph}	Photocurrent (A)
N_s	Number of cells connected in series
P	Power (W)
R_o	Parallel resistance (Ω)
R_s	Series resistance (Ω)
T	Temperature (K)
V_t	Thermal voltage of diode (v)
Greek symbols	
β	Temperature coefficient ($\%.^{o}C^{-1}$)
η	efficiency (%)
γ	Power coefficient ($\%.^{o}W^{-1}$)
Subscripts	
amb	ambient
module	module
ref	reference
Abbreviations	
ANN	Artificial neural network
BPNNs	Back-propagation neural networks
KNN	K-Nearest Neighbor
MRE	Mean relative error
MR-ESN	Multiple reservoirs echo state network
PCA	Principal Component Analysis
PV	Photovoltaic
RKRF	Reduced-Kernal Random Forest

RMSE	Root mean squared error
STC	Standard test condition
SVM	Support vector machine
WT	wavelet transform
MAE	Mean absolute error

1. Introduction

With the considerable growth in population all around the world, the need for higher energy production to meet people's demands is progressively increasing [1]. This point, in addition to the serious environmental concerns and the necessity of using economically justifiable ways has motivated the governments and policy-makers to invest on developing renewable energy systems, especially the solar energy [2].

Among a variety of selections to utilize the received energy from the sun, photovoltaic (PV) technologies have a great contribution to the market, and there have been several development plans for them in various parts of the globe [3]. In a PV system, the solar energy is directly converted into the electricity, while a part of the dissipated heat by PV system could be also recovered and used for heating purpose like domestic hot provision [4].

The place for installation of PV systems, especially in urban areas, are limited, and therefore, the appropriate design of them is necessary [5]. In addition, due to shading, and some other issues, the PV system might have some problems, which makes the necessity of choosing appropriate controlling and fault detection of them crystal clear [6]. Considering the challenges conventional methods have, and thanks to the huge progress in the computer science, machine learning prediction approaches are becoming popular in both design and operation control of PV infrastructure [7].

In designing a PV system, machine learning approaches have been employed to determine more accurate ways to obtain thermal and electrical behavior of system and covering the phenomena that are not covered by conventional modeling approaches [8]. In controlling PV systems, machine learning methods have been utilized for fault detection, while they could be also employed in trackers for defining a tracking strategy [9]. Such a great popularity of machine learning approaches has encouraged several researchers to conduct studies about them. A number of reviews have been also published during the recent years to cover the performed investigations.

As an example of such investigation, Akhter et al. [10] reviewed different methods for performance prediction of a PV module. In that study, different aspects, including the time resolution of the employed data, were considered. In addition, a number of studies done in the range of 2007 to 2018 with the topic of using machine learning methods such as artificial neural network (ANN) and support vector machine (SVM) were covered. Another review was also provided by Berghout et al. [11] to explain the application of machine learning approaches in monitoring the performance of PV systems. In [11], employing machine learning methods for detecting various fault in PV systems such as bridging, shading, and line to line problems, was investigated. An almost similar review paper was prepared by Kurukuru et al. [12], where the integration of thermal imaging and machine learning techniques was the topic. In addition, a review work was done by Yahya et al. [13] to review the work that have been done with the subject of PV module fault inspection using thermo-imaginary and machine learning ways. That study had a more focus on thermos-imaginary methods than machine learning.

By investigation of the literature, it has been found that, most of the review studies have investigated utilization of machine learning approaches for fault detection of PV systems. The review works that have been published by Dhimish [14], Kumaradurai et al. [15], Li et al. [16], Hwang et al. [17], Abdulmawjood et al. [18], Mellit et al. [19] could be given as some example of such works. Additionally, there have been some investigations, like Mosavi et al. [20], Tina et al. [21], de Freitas Viscondi et al. [22], Houssein et al. [23], Das et al. [24], Mosavi and Bahmani [25], and Ahmad et al. [26], in which using machine learning methods for prediction the performance of PV modules have been reviewed.

Furthermore, another part of the review studies in the field of PV, have investigated the research works which utilized machine learning prediction approaches for solar irradiance prediction. Some of the conducted reviews have been performed by Darío Obando et al. [27], Zhou et al. [28], Ağbulut et al. [29], Bamisile et al. [30], Al-Hajj et al. [31], and Fan et al. [32].

With the aim of providing a quick insight to available review works in the literature, Table (1) is provided in which some items have been checked for them. As it has been found from Table (1), there have been the following gaps in the review works:

- In most of the studies, the review has been done by considering one of the possible applications of machine learning in PV systems, i.e., either performance prediction, or fault detection, and so on. Therefore, there is the lack of a review study in which different applications have been reviewed and discussed, and the future perspective is drawn by taking all the applications into account.
- Another point is the conventional modeling approaches has not been investigated. Therefore, the review did not compare the conventional and machine learning approaches together to compare them in details.
- The focus in the conducted investigation has been on the technical aspects, including the used technique, number of the employed training, and validation set, the type of fault

detections, and so on. Consequently, the drawn perspectives have been on the technical side, as well. It implies that the environmental perspective has been overlooked, and the outcome of the review could not help to achieve the environmental and sustainability goals.

Consequently, the current review work is provided. Here:

- Both works with the topic of performance prediction and fault detection, and not only one of the topics, have been reviewed. It results in providing a broader insight for researchers, policy-makers, and investors to application of machine learning approaches, state-of-art, current trends, barriers, and future perspectives.

- In addition to the machine learning approaches, the conventional ways to analyze a PV system from both electrical and thermal aspects are also introduced and reviewed here. It leads to providing a framework for comparing the advantages and disadvantages of machine learning approaches in comparison to the conventional methods.

- Moreover, separate from the technical sides of machine learning approaches utilization, the review gives insights about the cleaner aspect and achieving the sustainability objectives. Therefore, a map for reaching the drawn environmental targets is presented.

Table (1): A list introducing the conducted review work in the field of application of machine learning for PV systems

Study	**Year**	**Did the review study consider application of machine learning in more than one application?**	**Did the review investigate the conventional modeling approaches from both thermal and electrical sides?**	**Did the review provide insights to the cleaner aspect and sustainable development?**
Akhter et al. **[10]**	2019	No	No	No
Berghout et al. **[11]**	2021	No	No	No
Kurukuru et al. **[12]**	2021	No	No	No
Yahya et al. **[13]**	2022	No	No	No
Dhimish **[14]**	2019	No	No	No

Kumaradurai et al. **[15]**	2019	No	No	No
Hwang et al. **[17]**	2021	No	No	No
Li et al. **[16]**	2021	No	No	No
Abdulmawjood et al. **[18]**	2020	No	No	No
Mellit et al. **[19]**	2018	No	No	No
Mosavi et al. **[20]**	2019	No	No	No
Tina et al. **[21]**	2021	No	No	No
de Freitas Viscondi et al. **[22]**	2019	No	No	No
Houssein et al. **[23]**	2019	No	No	No
Das et al. **[24]**	2018	No	No	No
Mosavi and Bahmani **[25]**	2019	No	No	No
Ahmad et al. **[26]**	2020	No	No	No
Darío Obando et al. **[27]**	2019	No	No	No
Zhou et al. **[28]**	2021	No	No	No
Ağbulut et al. **[29]**	2021	No	No	No
Bamisile et al. **[30]**	2021	No	No	No
Al-Hajj et al. **[31]**	2021	No	No	No
Fan et al. **[32]**	2019	No	No	No
The current work	**2022**	**Yes**	**Yes**	**Yes**

2. The conventional performance prediction ways

In general, the methods to estimate a PV system performance could be divided into two groups. One is the conventional ways which is referred to applications of either simple correlations or governing equations to analyze the performance of the system. Another is machine learning methods. Considering this point, in this part, the conventional ways to obtain electrical and thermal parameters of a PV module is discussed.

2.1.1. Thermal modeling

The goal of thermal modeling is to obtain the working temperature of a solar module or other performance criteria related to that.

2.1.2. Nominal operating cell temperature (NOCT)

The NOCT approach is the simplest way for predicting the working temperature of a PV module. It needs only the values of ambient temperature (T_{amb}) and received solar radiation (G). In NOCT approach, T_{module} is predicted based on Eq. (1):

$$T_{module,NOCT} = T_{amb} + \frac{G}{G_{ref}}(T_{NOCT} - T_{ref}) \quad (1)$$

NOCT temperature (T_{NOCT}) is one of the available items in the catalogue of each module. The 'ref' subscript denotes reference condition, as well. For the reference condition the temperature and irradiance values are 20 °C and 800 W.m^{-2}, respectively. The reference condition is not the same as the standard test condition (STC), which is the two indicated indicators have the values of 25 °C and 1000 W.m^{-2}, respectively.

2.1.3. Correlation approaches

Eq. (1) could be easily used for each solar module. However, it has some shortcomings, including:

- The modules from the same product family usually have the identical values of T_{NOCT}. Therefore, NOCT approach predicts the same value for all dimensions of a solar module product family. Due to changes in dimensions and consequently, the heat transfer rate, T_{module} is not equal for various module sizes from a product family when T_{amb} and G do not vary.
- In addition to T_{amb} and G, wind velocity (V_w) and relative humidity (φ) also affect T_{module}. Nonetheless, NOCT approach does not take them into account.

Consequently, some other correlations have been also provided during the recent years based on the experimental data. Table (2) introduces some of the most important ones. As seen, different functions have been developed. Among them, nominal module operating temperature (NMOT) is one the widely-used methods. It was given in IEC number 61853–2 for PV rating.

As another point, it is worth noting that, to the best of authors' knowledge, in a large number of presented correlations, relative humidity is not considered. However, in some of the recent studies, including Sohani et al. [33], the relative humidity has been also taken into account. In addition, it should be indicated that the used experimental data for adjusting the coefficients of a correlation should cover at least six months of a year, as mentioned in several references like [34]. Requiring long-term experimental data could be introduced as the most significant drawback of the correlation approaches, which is money and time consuming.

Table (2): Introducing the most important correlations that have been provided to predict the temperature of a PV module

Study	**Year**	**Ambient temperature (T_{amb})**	**Solar radiation (G)**	**Wind speed (V_w)**	**Relative humidity (φ)**	**The provided function for working temperature prediction (T_{panel})**
Ross [35]	1976	Yes	Yes	No	No	$T_{panel} = T_{amb} + 0.024G$
Scott [36]	1985	Yes	Yes	No	No	$T_{panel} = T_{amb} - 1 + 0.028G$
Servant [37]	1986	Yes	Yes	Yes	No	$T_{panel} = T_{amb} + 0.016G(1+0.030T_{amb})(1-0.085V_w)$
Lasnier [38]	2017	Yes	Yes	No	No	$T_{panel} = 30.006 + 0.0175(G-300) + 1.14(T_{amb}-25)$
Chenni et al. [39]	2007	Yes	Yes	Yes	No	$T_{panel} = T_{amb} + 0.0138G(1+0.031T_{amb})(1-0.042V_w)$
Kurtz et al. [40]	2019	Yes	Yes	Yes	No	$T_{panel} = T_{amb} + G\,e^{(-3.473-0.0594V_w)}$
Coskun et al. [41]	2016	Yes	Yes	Yes	No	$T_{panel} = 1.4T_{amb} + 0.01(G-500) - V_w^{0.8}$
Skoplaki et al. [42]	2008	Yes	Yes	Yes	No	$T_{panel} = T_{amb} + \left(\frac{0.25}{5.7+3.8V_w}\right)G$
Mondol et al. [43]	2007	Yes	Yes	No	No	$T_{panel} = T_{amb} + 0.031G - 0.058$
Skoplaki et al. [44]	2009	Yes	Yes	Yes	No	$T_{panel} = T_{amb} + \left(\frac{0.32}{8.91+2V_w}\right)G$
Almaktar et al. [45]	2013	Yes	No	No	No	$T_{panel} = 1.411T_{amb} - 6.414$
Risser and Fuentes [46]	1984	Yes	Yes	Yes	No	$T_{panel} = 0.899T_{amb} + 0.026175G - 0.00000754G^2 - 1.30V_w + 3.8621$
Muzathik et al. [47]	2014	Yes	Yes	Yes	No	$T_{panel} = 0.943T_{amb} + 0.0195G - 1.528V_w + 0.3529$

Tselepis and Tripanagnostopoulos [48]	2016	Yes	Yes	No	No	$T_{panel}=30+0.0175(G-150)+1.14(T_{amb}-25)$
Coskun et al. [49]	2017	Yes	Yes	Yes	No	$T_{panel}=T_{amb}+0.01632578G-0.8V_w+2.273$
Kalogirou [50]	2013	Yes	Yes	No	No	$T_{panel}=1.14(T_{amb}-T_{ref})+0.0175(G-300)+30$
Akyuz et al. [51]	2012	Yes	Yes	Yes	No	$T_{panel}=0.95T_{amb}+0.025G-0.3V_w+3.1$
Mora Segado et al. [52]	2015	Yes	Yes	Yes	No	$T_{panel}=T_{amb}+0.79\left[\frac{G}{G_{ref}}(T_{panel,NOCT}-20)\right]-1.52(V-V_{ref})$
King [53]	2009	Yes	Yes	Yes	No	$T_{panel}=T_{amb}+\frac{G}{G_{ref}}(0.0712V_w^2-2.411V_w+32.96)$
PV rating IEC 61853-2 [54]	2009	Yes	Yes	Yes	No	$T_{panel,NMOT}=T_{amb}+G\frac{1}{u_0+u_1V_w}$
Standard 61215 [55]	2015	Yes	Yes	No	No	$T_{panel,NOCT}=T_{amb}+\frac{G}{G_{ref}}(T_{NOCT}-T_{ref})$
Sohani et al. [33]	2020	Yes	Yes	Yes	Yes	$T_{panel}=\frac{1}{3}\left\{aT_{amb}+b(\frac{G}{G_{ref}})^c+d\varphi^e+fV_w+g\right\}-273.15$

2.1.4. One dimensional (1D) numerical approach

In 1D numerical approach, a module is considered as a number of layers (Figure (1)). Then, for the whole points on a layer, the same temperature value is assumed, and by solving the governing equations, the temperature of each layer is determined.

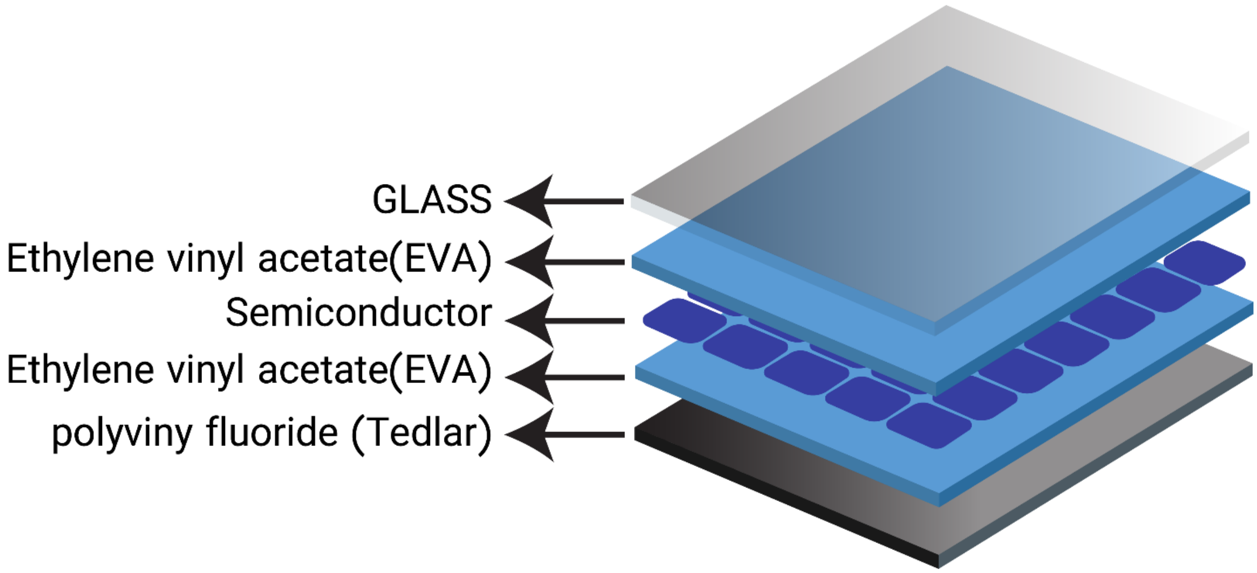


Figure (1): The considered five layers of a PV module in 1D numerical modeling [56]

In comparison to NOCT, NMOT, and other correlation approaches, 1D is more accurate due to the fact that it considers the governing equations. However, number of needed inputs is much more than the previously indicated approaches. The thickness of layers, as well as their isobaric heat capacities and densities are some of them. An overview of the studies in which 1D numerical modeling has been either developed or utilized is provided in Table (3). As this table indicates, the temperature dependency of the layers' properties, including isobaric heat capacity and density have been neglected in most of the studies. Nonetheless, as it has been shown in [56], considering the indicated properties as a function of temperature could enhance the accuracy of modeling considerably. It is worth noting that number of the studies in which 1D numerical model has been employed is lower than other approaches.

Table (3): An overview of the conducted investigations with the topic of 1D numerical modeling of a PV system

Authors	Year	The investigated system	The conducted analysis	Was temperature dependency of thermal properties considered?
Tomar et al. [57]	2018	Building integrated photovoltaic thermal (BIPVT) unit	Parametric study	No

Osma-Pinto and Ordonez-Plata [58]	2020	Photovoltaic thermal technology	Parametric study	No
Singh et al. [59]	2019	Photovoltaic thermal technology	Parametric study	No
Gu et al. [60]	2019	Photovoltaic technology	Parametric study	No
Shahsavar et al. [61]	2020	Photovoltaic thermal technology	Parametric study	No
Shahverdian et al. [62]	2021	Photovoltaic thermal technology	Optimization	No
Sohani et al. [56]	2021	Photovoltaic technology	Parametric study	Yes; all layers except for Tedlar layer

In addition to higher number of needed input parameter to run, more run-time and requiring to have a background from to the governing equations are taken into account as the most serious challenges of 1D numerical approach. As the most remarkable drawback, 1D is not able to consider temperature distribution on the surface of module, which numerical models with higher dimensions do.

2.1.5. 2 and 3 dimensional (2D and 3D) numerical techniques

When 2D and 3D numerical techniques are employed, the temperature distribution on the module surface could be obtained. It is done by writing and solving the governing equations, including energy and momentum equations. List of the recent studies with the subject of 2D and 3D numerical modeling of a PV system is presented in Table (4).

Table (4): List of the recent studies with the subject of 2D and 3D numerical modeling of a PV system

Study	Year	Module type	Modeling dimension	The compared engineering methods	Temperature distribution related criteria
Zondag et al. [63]	2002	Poly crystalline (PC)	1D, 2D, and 3D	N.A.	N.A.
Pierrick et al. [64]	2015	Mono crystalline (MC)	3D	N.A.	Module mean temperature
Usama Siddiqui et al. [65]	2012	MC	3D	NOCT	Module mean temperature
Paradis et al. [66]	2017	MC	2D	N.A.	Module mean temperature
Guarracino et al. [67]	2016	MC	3D	N.A.	N.A.
Hosseinzadeh et al. [68]	2018	MC	3D	N.A.	N.A.

Nasrin et al. [69]	2018	PC	3D	N.A.	Module mean temperature
Amanlou et al. [70]	2018	MC	3D	N.A.	Module mean temperature
Yamamoto et al. [71]	2018	MC	2D	N.A.	N.A.
Fayaz et al. [72]	2019	PC	3D	N.A.	Module mean temperature
Maadi et al. [73]	2019	PC	3D	N.A.	Module mean temperature
Kazemian et al. [74]	2019	MC	3D	N.A.	Module mean temperature
Atsu and Dhaundiyal [75]	2019	Poly and mono crystalline, as well as amorphous thin film Si-based modules,	2D	NOCT	N.A.
Hu et al. [76]	2020	MC	2D	N.A.	N.A.
Salari et al. [77]	2020	MC	3D	N.A.	Module mean temperature
Abd El-Samie et al. [78]	2020	PC	3D	N.A.	Module mean temperature
Salameh et al. [79]	2021	PC	3D	NOCT	Module mean temperature
Sohani et al. [80]	2021	MC and PC	1D, 2D, and 3D	NOCT and NMOT	Changes in prediction error by variation of σ

Considering the fact that 2D and 3D numerical approaches solve the governing equations in a way that they provide the temperature distribution on the module surface, they are more accurate than 1D numerical, NOCT and other correlation approaches. However, they impose more computational cost and time, while using them requires having the knowledge about a number of processes including heat and mass transfer. They also need more input parameters than others to run.

2.2. Electrical modeling

The purpose of electrical modeling is to determine power as the main output of the system. Voltage and current are also other parameters which could be determined by electrical modeling.

2.2.1. Correlation approach

In most of the studies, when the goal is to obtain the power, and not more electrical parameters like voltage and current, Eq. (2) is first employed to determine the efficiency. Then, in order to calculate power, efficiency (η) is multiplied by the received solar radiation (G) and module area (A_{module}), which are known parameters:

$$P = \eta G A_{module} \tag{2}$$

$$\eta = \eta_{ref}\left\{1 - \beta_{ref}(T_{module} - T_{ref}) + \gamma \log_{10}(G)\right\} \tag{3}$$

T_{module} is a known parameter, which could be obtained from thermal modeling. In addition, η_{ref} is the efficiency of module in the reference condition, while γ stands for the coefficient for the condition with the maximum power. Both η_{ref} and γ are usually available in the module catalogue.

2.2.2. The equivalent circuit method

In case more electrical parameters than power, e.g., are going to be determined, the equivalent circuit method could be utilized. In this method, the electrical performance of the module is described using an equivalent circuit which is composed of a number of diodes and resistances. Three important items in each equivalent circuit are:

- Photocurrent (I_{ph}): It describes the amount of current generated by the received solar radiation.

- Series resistance (R_S): A part of produced energy by the solar module is dissipated during passing the current through the semiconductor and connections that are made of metal. R_S is used to describe that.

- Parallel resistance (R_P): Parallel resistance, which is also known as shunt resistance, is used to cover a number of phenomena, such as passing the current from the module's edges, crystal geometry holes and non-idealities.

2.2.2.1. Single diode model

Here, which is also called the one diode approach, an equivalent circuit like Figure (2a) is considered. As observed, this equivalent circuit is composed of a series resistance, a shunt resistance, and a current source that describes the produced photocurrent. In addition to the mentioned items, there is also a diode in the circuit. A part of the produced current by light goes into the diode, which decreases the received the voltage at terminals. Based on the electrical governing rules, in single-diode model, the relation between the current and voltage is [81]:

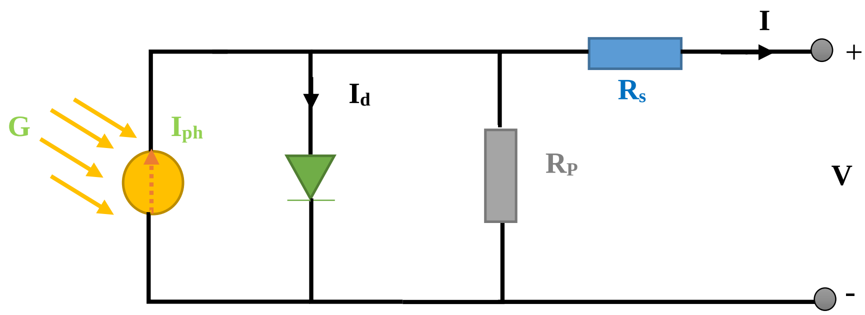
$$I = I_{ph} - I_0\left[\exp\left(\frac{1}{V_t}\left(\frac{V}{N_S} + I.R_S\right)\right) - 1\right] - \frac{1}{R_p}\left(\frac{V}{N_S} + R_S I\right) \tag{4}$$

As observed, in addition to I_{ph}, R_S, and R_P, there are three other important parameters in the equations. They are [7]:

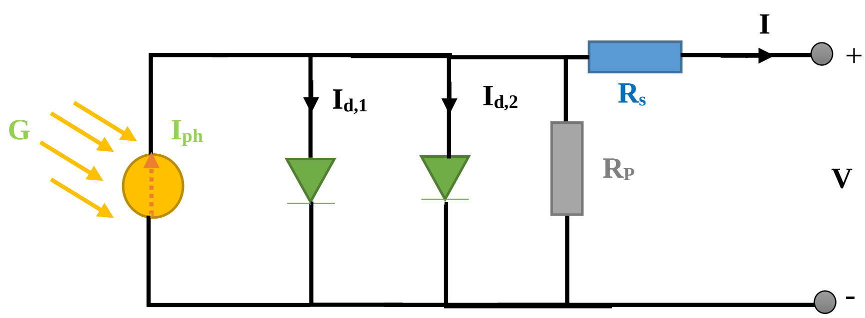
Thermal voltage of diode (V_t): Thermal voltage of diode describes the thermal driving force of electrons in a semi-conductor to move. However, this movement is the opposite direction of photocurrent.

Diode saturation current (I_0): This parameter describes the movements of minority of charge carriers in a semi-conductor from neutral to depletion area.

Number of connected cells in series in a module (N_S): A module is built by connecting a number of cells that are electrically in series.



(a)



(b)

Figure (2): The diode equivalent circuit; (a) single diode approach; (b) double diode approach

In addition to the voltage and current, other parameters in Eq. (4) are obtained from Eqs. (5) to (9):

$$R_p = \frac{G_{STC}}{G} R_{p,STC} \tag{5}$$

$$R_s = R_{s,STC} \tag{6}$$

$$I_0 = I_{0,STC} \left(\frac{T_{module}}{T_{module,STC}}\right)^3 \exp\left[\frac{qE_g}{K}\left(\frac{1}{T_{module,STC}} - \frac{1}{T_{module}}\right)\right] \tag{7}$$

$$V_t = \frac{T_{module}}{T_{module,STC}} V_{t,STC} \tag{8}$$

$$I_{ph} = \frac{G}{G_{STC}}\left\{I_{ph,STC} + \alpha(\mathrm{T}_{module} - \mathrm{T}_{module,STC})\right\} \tag{9}$$

As seen, in order to determine the values at the investigated condition, the values at STC are required. The values of I_0, V_t, and I_{ph} at STC are calculated according to Eqs. (10) to (12) [82]:

$$I_{0,STC} = I_{\mathrm{sc},STC} \exp(\frac{-V_{oc,STC}}{N_s V_{t,STC}}) \tag{10}$$

$$V_{t,STC} = \frac{\beta T_{module,STC} - V_{oc,STC}}{\frac{N_s T_{module,STC}\,\alpha}{I_{ph,STC}} - 3N_s - \frac{E_g N_s}{K T_{module,STC}}} \tag{11}$$

$$I_{ph,STC} = I_{\mathrm{sc},STC} \tag{12}$$

The parameters on the right-hand side of Eqs. (10) to (12) are known. They are either the available module characteristics in the module catalogue (like $I_{\mathrm{sc},STC}$, $V_{oc,STC}$, β, and α) or constant parameter (like E_g and K). In addition, the value of series resistance at STC is computed by solving Eq. (13), in which this parameter is the only unknown variable:

$$\begin{aligned} I_{\mathrm{mp},STC} = {} & I_{ph,STC} - I_{0,STC}\left[\exp(\frac{V_{\mathrm{mp},STC} + I_{mp,STC} R_{\mathrm{s},STC}}{N_s V_t}) - 1\right] \\ & - \frac{(V_{\mathrm{mp},STC} + I_{mp,STC} R_{\mathrm{s},STC})\left[-N_s V_{t,STC} I_{mp,STC} + (V_{\mathrm{mp},STC} - I_{mp,STC} R_{\mathrm{s},STC})(\mathrm{I}_{\mathrm{sc},STC} - I_{mp,STC})\right]}{(-I_{mp,STC} R_{\mathrm{s},STC} + V_{\mathrm{mp},STC})(V_{\mathrm{mp},STC} - N_s V_{t,STC})} \end{aligned} \tag{13}$$

The shunt resistance at STC could be also determined from Eq. (14):

$$R_{\mathrm{p},STC} = \frac{(-I_{mp,STC} R_{\mathrm{s},STC} + V_{\mathrm{mp},STC})(V_{\mathrm{mp},STC} - N_s V_{t,STC})}{-N_s V_{t,STC} I_{mp,STC} + (V_{\mathrm{mp},STC} - I_{mp,STC} R_{\mathrm{s},STC})(-I_{mp,STC} + \mathrm{I}_{\mathrm{sc},STC})} \tag{14}$$

2.2.2.2. Double diode model

One of the effective factors in a PV module, which is similar to a diode, is the ideality factor. One the one hand, at lower voltage range, the ideality factor is close to 2 due to domination of junction recombination. One the other hand, at higher range of voltage, the ideality factor approaches the unity since the dominant process is recombination by bulk area and surfaces of PV. In the single diode model, the ideality factor is considered constant. Nonetheless, by adding another diode in parallel with the available one in the single diode model, modeling gets more accurate in the double diode model (Figure (2b)). The equations for the double diode model is quite similar to the single diode with only some modifications because of adding the second diode. They could be found in the references, like the studies of Babu and Gurjar [83], Shannan et al. [84], Chennoufi et al. [85], and Sangeetha et al. [86].

2.3. Problems of the conventional approaches

Despite being widely used, the conventional approaches suffer from some drawbacks. The first and foremost is the simple correlations for thermal modeling do not consider a number of effective parameters such as relative humidity, while they are mostly accurate for one module, and they could not be generalized [87]. In addition, in the more advanced thermal modeling approaches, like 1D, 2D, and 3D numerical approaches do not consider some issues like hot spots on the surface of module, which leads to high difference between the actual and predicted working temperature values. Moreover, there have been several challenges in parameter estimation of the equivalent circuit method. It makes using it with serious difficulties. As a result, machine learning approaches is being increasingly utilized for PV systems. Not only are they employed for performance prediction from both electrical and thermal sides, they are also utilized for fault detection, as it will be discussed in the next part.

3. Using machine learning approach for PV systems

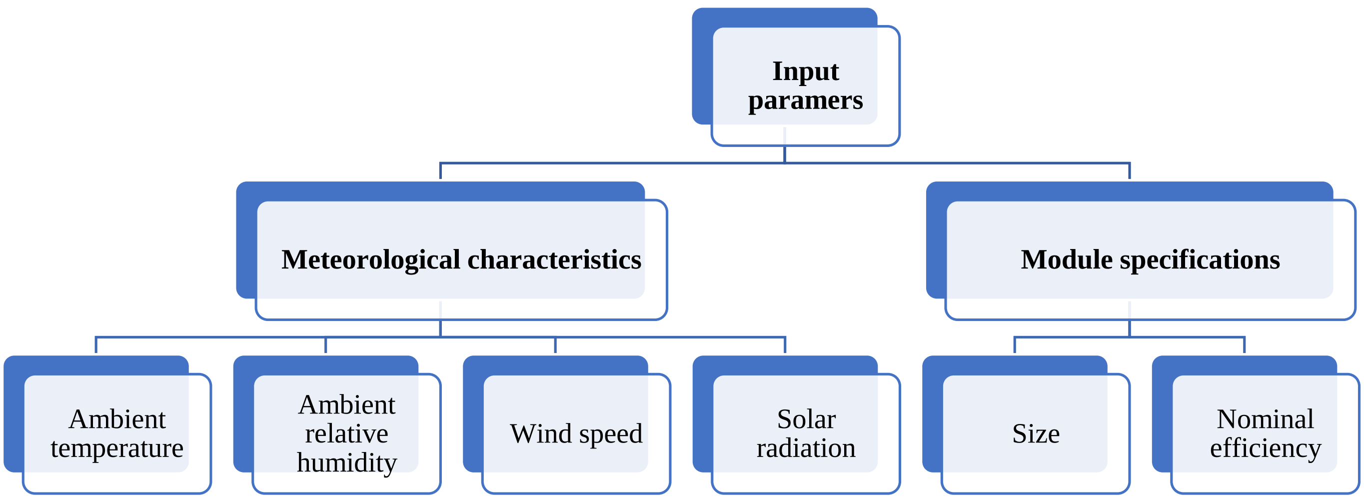
As it has just mentioned, machine learning approaches are being increasingly employed for PV systems. It is done with two purposes. One is the performance prediction, while fault detection is another usage of machine learning approaches for PV systems.

3.1. Performance prediction

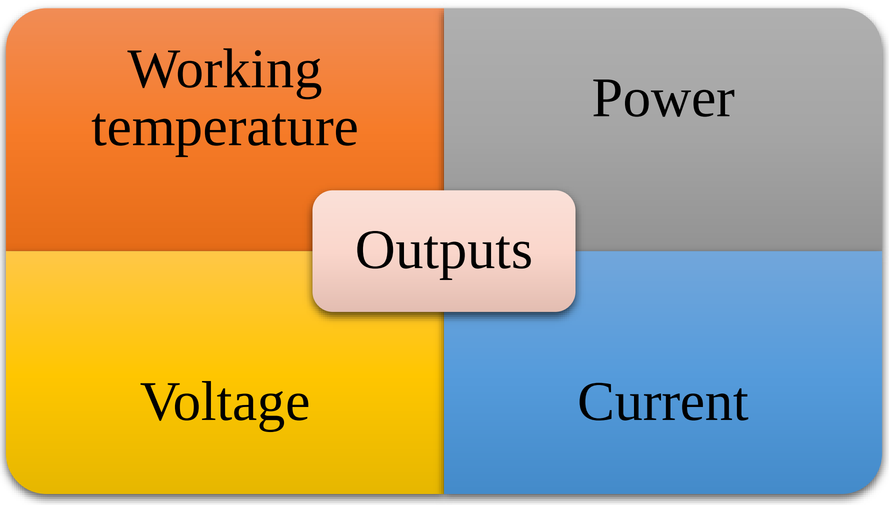
Performance prediction is one of the most important applications of machine learning approaches for PV installations. It could be done with the aim of determination of one or more than one parameter from the following list (Figure (3)):

- Working temperature,
- Voltage,
- Current,
- Power.

The input parameters of those models have been usually the meteorological parameters, as well as a number of module specifications [88]. As an example of the conducted investigations, Han et al. [89] considered a ELM-based multi system to predict the power generated at a photovoltaic plant in Beijing, China. Using the developed prediction tool, the mean absolute errors were 1.70% in hot season and 2.13% in spring, but using the single model, the corresponding values were 1.81% and 2.43%, respectively. Therefore, the developed prediction tool estimated the power more accurately.



(a)



(b)

Figure (3): Showing the input parameters of machine learning methods for performance prediction of a PV power production system; (a) input parameters; (b) outputs

In [90], a model which had been developed using multiple reservoirs echo state network was used to predict photovoltaic power. In this model, which was briefly called MR-ESN, the reservoir parameters were optimized by the quasi-Newton algorithm. According to the results, the MAPE value was 0.00195%, which is very close to zero. This model was more accurate than others such as conventional neural networks, like BPNN, wavelet transform (WT), support vector machines (SVM), and support vector regression (SVR-ANN).

Al-Dahidi et al. [91] used an ELM algorithm to use in the MLP network to predict the power of a PV power plant in Amman, Jordan. With this method, the lowest mean absolute error was 1.08% in June and the highest mean absolute error was 18.83% in February and March.

In order to predict the performance of a Chinese photovoltaic power production system which was located in Beijing, SVM and MLP methods are used [92]. Based on this research, the model used is very useful, especially for different circumstances with mist and fog. Air temperature and relative humidity were among the inputs of the model.

A new method based on satellite and NWP data was developed to forecast the generated electricity of a photovoltaic power production sytem installed in Italy [93]. The verification was done with a small-scale photovoltaic solar power production in Tyrol, Italy. For a 4-hour time horizon, the RMSE was between 5% and 7% and for one day, it was in the range of [7% -7.5%]. Leva et al. [94] provided an MLP-based model for predicting photovoltaic performance using weather data. This method worked better on sunny days than on cloudy days. Das et al. [95] used a SVM-based model to predict photovoltaic power generation. In Malaysia, this model was validated in different weather conditions including clear, cloudy and rainy. The mean absolute error was 34.57%.

Paulescu et al. [96] predicted the electricity production of 2 photovoltaic production systems in Catania and Milan in Italy using a fuzzy logic based approach. The average absolute errors were 0.64 and 0.56 kW for Milan and Catania, respectively. In that study, the studied model had better accuracy in the hot season than the cold time of the year.

A fuzzy T-S method was presented in [97] to predict the photovoltaic approach. The inputs to this method were meteorological parameters. The comparison of the found prediction tool was done with other methods. According to the results, the provided prediction tool had the lowest absolute error in summer and the highest average error in spring, which is 9.77% and 30%, respectively.

Li et al. [98] used a hierarchical approach to achieve system performance. Various parameters such as power and system geometry were used as inputs. The methods based on ANN and SVR were more accurate than other methods. In addition, Sohani et al. [99] employed ANN to predict the electrical characteristics of 2 PV modules. One poly and one mono crystalline module were considered, with almost the identical dimensions. Each of them had the capacity of 50 W. Relative humidity was one of the inputs for ANN. A parametric study was then conducted using ANN to discover the sole impact of relative humidity on the system operation.

A quick summary of the most important items of the indicated studies for performance prediction of PV modules is presented in Table (5).

Table (5): A quick summary of the most important items of the indicated studies

study	Year	Method	Accuracy
Li et al. [98]	2016	ML-H	Mean absolute error = 128.77 kWh
Leva et al. [94]	2017	ANN	Mean absolute error < 15%
Das et al. [95]	2017	SVM	Average mean absolute error = 34.57%
Liu et al.[92]	2018	ANN and SVM	Mean regression error = 11.61%
Liu et al. [97]	2017	FL	Mean absolute error= 0.56 and 0.64 kW
Al-Dahidi et al. [91]	2018	ANN-ELM	Mean absolute error = 1.08%
Han et al. [89]	2019	ELM	Mean absolute error = 2.13%
Yao et al. [90]	2019	ESN	Mean absolute prediction error = 0.00195%
Sohani et al. [99]	2021	ANN	Mean absolute error = 3.21%
Pierro et al. [93]	2017	ANN	Root mean square error = five to seven percent for one to four hours

Paulescu et al. [96]	2017	FL	Root mean square error = seven to seven and a half for one to two days MAE = 9.77%

3.2. Fault detection and solving that

According to the information provided in several references such as Sabbaghpur et al. [100], and Berghout et al. [101], from different possible faults for a PV system, six items are more important. They are (Figure (4)):

- Shading,
- Degradation,
- Bypass diode,
- Line to line,
- Open circuit,
- Bridging

In this part, the explanation about each item is given briefly, and then, some machine learning based solution that have been provided in the literature are introduced.

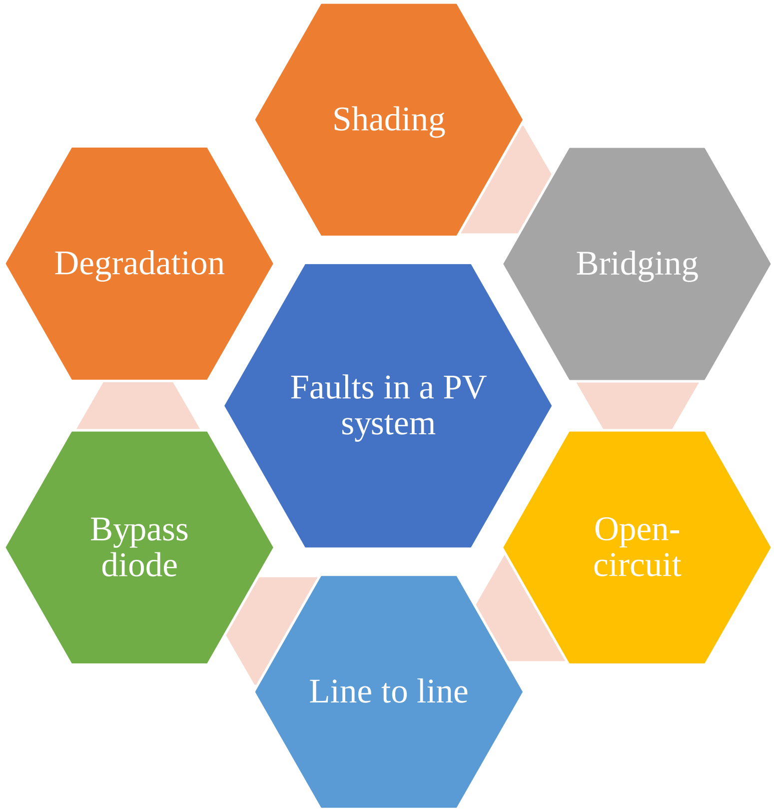


Figure (4): Different common faults in a PV system

3.2.1. Shading

The performance of a PV system has a direct relationship with the received solar radiation. Therefore, when there is shading on a part or the whole module, its generated power goes down. Shading could originate from different things, including the soil and dirt, or the objects such as trees, the buildings in surroundings, or even other panels.

One of the solutions that could be employed to solve the shading problem is diode bypassing. Diode bypassing refers for isolation of modules with shading from other ones. Another way is controlling the modules orientation to have the least shadow level and highest energy production, while finding the foremost arrangement (number of series and parallel modules) is taken into account as another way to deal with the issue.

As an example of the studies in which shading detection has been done and a solution for dealing with has been presented, Huang et al. [102] provided an ANN that was composed of 1 hidden layer. Extreme machine learning was the training algorithm, in which the Bee Colony method was used. The found ANN was then utilized to detect shading come from dust and dirt. Another investigation in the field was carried out by Maaløe et al. [103], where Bayes Theorem was utilized for clustering various types of faults that originate from shading. The developed simulation procedure took advantage of I-V characteristics to find the difference between several operating modes. It has been typical to investigate the degradation in addition to the shading faults in the studies.

3.2.2. Degradation

Like any other device, the performance of a PV system declines. This process, which is called degradation, comes from different issues in a solar module, such as breaking the glass, hot spots, bubbles, encapsulant discoloration, delamination, ribbon discoloration, and so on. In general, it is estimated that, on average, around 0.8% reduction in the performance of a solar module is seen every year [104]. According to the information provided in [104], among the indicated items, hot spots have the highest contribution (33%) to the degradation. Not only do hot spots have negative effect on the performance, they also cause difference between the model prediction and reality, as completely discussed in the previous parts. Ribbon discoloration is taken into account as the second significant factor, with 12%. Breaking glass and encapsulant discoloration are in the third and fourth places, respectively. They are responsible for 10 and 9% of degradation, respectively.

Ali et al. [105] conducted a study with the aim of investigation of hot spots effects on a PV module operation. In that study, photos taken by an infrared camera were employed, while a number of methods for parameters specifications, as well as a variety of image processing techniques, including texture, RGB, OGH, and LBP were examined. Evaluation of different methods using a number of datasets had shown that the support vector machine (SVM) was superior to the other machine learning approaches in prediction. Another similar work was done by Dhimish [106] a more advanced method that is called discriminate classifiers had also a higher capability of accurate prediction that the conventional machine learning approaches like SVM.

3.2.3. Open circuit

If a wire in a PV system does not transfer the current, the open circuit happens. Open circuit comes from different issues such as fuse blowing, terminal problems, connection faults, and cutting a wire [107]. As indicated in several references, such as [108] of the open-circuit has more harmful effects than the short-circuit condition due to the increasing growth in the amperage flow. However, reviewing the literature has demonstrated that machine learning approaches has been rarely employed for open-circuit fault detection. In the few studied cases, it was not studied separately, and it was investigated beside some other types of faults.

For instance, Dhibi et al. [109] employed a number of machine learning approaches, including KNN, PCA, and Reduced-Kernal Random Forest (RKRF) to provide a means for detecting a number of faults in a PV system, such as open-circuit. Data collection was done by installation of 9 sensors to capture current and voltage. The study covered the shading and line to line faults in addition to the open-circuit one, as well.

3.2.4. Line to line

When the ions content in the air reaches a threshold value, or when an accident contact between lines occurs, the line to line fault happens. It leads to providing a path with small impedance for passing the current thorough, and it may cause serious harmful effects [110]. According to the explanations available in [111], three are three methods for detection of this fault, which are processing signals, machine learning, and combined approaches. Reviewing the literature has demonstrated that number of studies which have utilized machine learning techniques for detection of this fault, is more than other ones.

The investigation done by Eskandari et al. [112] could be given as an example of such studies, in which a number of different techniques for finding a suitable prediction way, such as SVM, KNN, and Naive Bayes were employed. In addition, in another similar study, Eskandari et al. [113] evaluated some more methods with higher accuracy for detection of this type of fault. Gao et al. [114] also used CNN to select fault from 10 defined modes, including the shading and line to line types. Their method was developed in a way that it has the ability of training in an online way.

3.2.5. Bridging

If there were some problems in the PV system structure or wiring, the resistance between two points might be low, and it leads to short circuit and harms the PV system [115]. This fault is usually detected by analyzing power voltage characteristic curves [116]. Like line to line fault, number of the studies in which bridging fault is found and analyzed by machine learning approaches has been considerably lower than ones. The work done by Harrou et al. [117] is an example of such investigations. In that reference, a variety of machine learning methods, like Gaussian process regression, SVM, and kernel mapping method had been examined for identification of six types of faults, including bridging.

3.2.6. Bypass diode

As explained, when there is shadow on a number of modules, the performance of them declines considerably, which affect the whole PV system performance. By installing bypass diodes, this problem could be solved, and the modules or cells with the shadow will be put aside [118]. If these diodes had a problem, the system performance would reduce.

In contrast to shading and degradation which are the common investigated types of faults, bypass diode fault detection has been rarely done. The reference [117] is one of such research works. Table (6) provides a brief summary of the recent conducted studies with the topic of fault detection in PV systems.

Table (6): a brief summary of the recent conducted studies with the topic of fault detection in PV systems

Study	Year	Number of faults	Type of considered faults	The employed machine learning approaches
Bakdi et al. [119]	2021	Sixteen	Open-circuit and shading	Kullback–Leibler Divergence, PCA, and Recursive Smooth Kernel Density
Maaløe et al. [103]	2020	Ten	Shading	Bayes' theorem
Li et al. [120]	2019	Five	Shading and degradation	SVM and Convolutional neural Networks (CNN)
Rahman et al. [121]	2020	Two	Degradation	SVM, Naive Bayes, and KNN
Dhibi et al. [109]	2020	Two	Degradation	PCA, Reduced-Kernal Random Forest, and KNN
Pierdicca et al. [122]	2020	Three	Degradation	CNN
Eskandari et al. [112]	2020	Two	Line to line	Naive Bayes, KNN, and SVM
Edun et al. [123]	2020	N.A.	Line to line	SVD
Ali et al. [105]	2020	Two	Degradation and shading	SVM
Venkatesh et al. [124]	2021	Five	Degradation	CNN

4. Role of machine learning approaches in achieving cleaner aspect and environmental targets

More accurate prediction of power produced by PV system leads to more precise sizing of the system. Moreover, when working temperature of a module is found more accurately, better thermal management way could be suggested to decrease the system performance. As a result, a constant value of power could be supplied by a lower PV module area and higher efficiency. As a result, the PV environmental PV impact during its life time goes down considerably, while the goal to achieve higher efficiency energy systems is achieved. It should be noted that since a large part of the produced environmental emission of a PV system comes from its production and disposal, the major studies in the field of environmental assessment of PV technologies to have a cleaner performance have employed life-cycle assessment (LCA) method for this purpose. LCA has been utilized in several studies, including the research works of Saedpanah et al. [125], Fardi Asrami et al. [126], Sumper et al. [127], and Azzopardi and Mutale [128]. Moreover, there are some good review works that have covered application of machine learning approaches for PV systems, including Parida et al. [129] and Hussien Rabaia et al. [130].

Additionally, machine learning approaches could help to better operation of PV technologies, and less degradation of them. Moreover, the time of being a PV system in operation goes up by applying suitable fault detection methods in which machine learning methods are utilized. Consequently, the need for producing power in fossil-fuel based power plants and number of modules should be replaced during the life span decline. Therefore, both life-cycle emission and electrical energy production have upward trends. Therefore, using machine learning methods could much effectively help to achieve the energy and environmental milestones.

5. The future perspective: challenges and outlook

The conducted literature review has demonstrated that machine learning techniques are being employed for both performance prediction and fault detection of PV systems more and more. As observed, the neural network-based methods have been the dominant ones, whereas some other techniques like SVM is also taken into account as effective widely-used means.

One of the serious challenges about machine learning approaches is overfitting. The overfitting is the appropriate operation withing a limited range of data and not having a suitable performance outside the range. In order to solve the issue, number of the input data could increase, while the range of the effective parameters should be extended as far as possible. For the cases which could not be by the experimental data, simulators, or appropriate simulation ways could would be suggested.

Another challenging point about using machine learning prediction tools is connection among different parts, as well as the employed infrastructure. Based on the huge development in the Internet of Things (IoT), the sensors and systems based on them would have a greater contribution in the field. In addition, using wireless networks and connection to the robots which are responsible for cleaning the module surface is becoming more popular. The imposed cost of infrastructure, including the computational parts and other devices could be made up using the enhancement in the energy and environmental benefits of the system. This would accelerate by reduction in the cost of PV system in the future, as predicted in several references like [131]. The indicated great positive impacts will lead to extension of using machine learning approaches from the PV solar farms on the big-scales to the small-scale PV installations, such as rooftop and BIPV/T systems.

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Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: