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A Comprehensive Review And Comparative Analysis Of Photovoltaic Performance Modeling Techniques

Bhupendra Kumar
Research Scholar, Electrical Engineering Department, University Institute of Technology, RGPV Bhopal
Dr. Narayan P. Gupta
Assistant Professor, Electrical Engineering Department, University Institute of Technology, RGPV Bhopal

Abstract:

This paper presents a comprehensive review and comparative analysis of photovoltaic (PV) performance modeling techniques, categorizing them into mathematical, analytical, and computational approaches. It examines the strengths and limitations of each category, focusing on their ability to accurately simulate and predict PV system behavior under diverse environmental conditions. Mathematical models offer simplicity and closed-form solutions, while analytical models provide deeper physical insights through fundamental equations. Computational models, leveraging advanced numerical methods and machine learning, demonstrate enhanced adaptability and robustness. The review highlights the evolution of modeling techniques, emphasizing the trend towards incorporating dynamic environmental factors and advanced computational methods. It also identifies critical research gaps, including the validation of models under extreme conditions, the development of dynamic models, and the quantification of uncertainties. The paper concludes by emphasizing the importance of selecting an appropriate modeling approach based on specific application requirements and underscores the potential of hybrid models for achieving improved accuracy and reliability in PV system performance prediction.

Keywords: PV Cell Modeling, Mathematical Modeling, Analytical Modeling, Computational Modeling, Irradiance Modeling, Temperature Modeling, Power Forecasting

1. Introduction

Energy is considered to be the life line of modern economic progress and fundamental need for the current standards [1]. From few decades there is seen that the population is grown exponentially and the consumption as well as demand also simultaneously higher than the generation from the conventional station [2]. Presently, these need relay on the conventional generating station which is fossil fueled and emitting lots of carbon in environment. Increasing the energy demand of the growing population, limitation of conventional or non-renewable energy sources, sustainable long term methods should be adopted which is the adoption of renewable power sources [1]. Fossil fuel are finitely and exhaustive in nature but the non-conventional sources are affordable, abundantly available for the reduction of carbon footprints. Energy sources such as wind energy, hydro energy, solar energy, etc., are the prominent contributor of energy generation nowadays. However, these sources also have some limitations i.e., non-linearity, inconsistency, intermittency, location dependency, meteorological dependency made to think of return on investment and reliability of the system [2].

Presently, the installed capacity power generation is generally based on wind and hydro but the energy potential of solar is more than other renewable sources, also solar energy is inexhaustible and presents everywhere. Solar energy is the most viable sources for the reduction of fossil fuel-based power plant and shifting of load demands towards renewable sources [1]. Solar energy is converted to electrical energy by the help of PV cells. However, these sources are also comes with their demerits of the performance may vary on different environment condition. To overcome the situation, many ways are proposed, one approach includes the utilization of manufacturer's data whose provide the detailed performance of the model but only relaying on these data may affects the output power prediction. So for that predictive models proposed by many researchers helps in maintaining the accuracy of the prediction [1]. These PV cells need accurate modeling for the estimation of maximum yield generated from them; also accurate modeling provides data for the prediction of the electrical output power for determination of the performance.

Currently, there are many predictive models are proposed by many publications; also all of the models have their own significance in the determination of performance of the PV cells. It is somehow difficult to say which model is better than the other model. So in this paper, some models are discussed and compared on the outcomes of their proposed models with manufacturer's datasheet, so that it is easy to understand the most significant model with less error for the estimation of the performance of the PV cells.This article is organized as follows; section 1 is introduction of the article, section 2 details about the basic models of the PV cells, section 3 discussed various proposed models, section 4 presents the analysis and discussion regarding the comparative analysis. and then the final section 5 conclusion of the article.

Abbreviations and Acronyms:

- PV: Photovoltaic
- SDM: Single Diode Model
- DDM: Double Diode Model
- TDM: Triple Diode Model
- STC: Standard Test Conditions
- MPPT: Maximum Power Point Tracking
- NR: Newton Raphson
- AGA: Adaptive Genetic Algorithm
- ANN: Artificial Neural Network
- SVM: Support Vector Machine
- DDE: Delay Differential Equation
- I_{ph}: Photo-generated current
- I_o: Diode saturation current
- R_s: Series resistance
- R_{sh}: Shunt resistance
- n: Ideality factor

2. Basic models of the PV cells

The first stage of modeling of PV cell is based on the number of diodes incorporated inside the PV cell. There are generally three models are considered as basic circuit of PV cell, single diode, double diode and triple diode model, these are used to represent the electrical behavior of the PV cell. Each model has their merits and demerits in the accurate representation of the electrical behavior of the PV cell.

2.1. Single Diode Model (SDM): SDM is a fundamental electrical model used to represent the behavior of a PV cell. It is a basic form for the prediction and optimizing the performance. This model provides relatively simple, accurate behavior of the PV model. Since it is widely used because of simplicity. For higher accuracy and under varying temperature and irradiance conditions, DDM may prefer [20,22,31]. The output current equation is given by:

$$I = I_{ph} - I_0\left(e^{\frac{V+IR_s}{nV_t}} - 1\right) - \frac{V+IR_s}{R_{sh}} \tag{1}$$

2.2. Double Diode Model (DDM): DDM is an enhanced electrical model of a PV cell, designed to provide greater accuracy than SDM. For certain a behavior of PV cells like low irradiance DDM addresses these limitations and accurate fit to the actual I-V characteristics. It introduces additional parameters, such as the ideality factor and saturation current of the second diodes [20,38]. The output current equation is given by:

$$I = I_{ph} - I_{01}\left(e^{\frac{V+IR_s}{n_1V_t}} - 1\right) - I_{02}\left(e^{\frac{V+IR_s}{n_2V_t}} - 1\right) - \frac{V+IR_s}{R_{sh}} \tag{2}$$

2.3. Triple Diode Model (TDM): TDM builds upon by the adding a third diode to the equivalent circuit, each added diode accounts for different types of recombination loss. It provides the highest level of accuracy among these diodes based models. It is helpful in detailed analysis of PV cell performance under various operating conditions. Since, the number of the parameters that need to be determined increases, this makes more complex to implement and more efforts for parameters extraction [45,46]. The output current equation is given by:

$$I = I_{ph} - I_{01}\left(e^{\frac{V+IR_s}{n_1V_t}} - 1\right) - I_{02}\left(e^{\frac{V+IR_s}{n_2V_t}} - 1\right) - I_{03}\left(e^{\frac{V+IR_s}{n_3V_t}} - 1\right) - \frac{V+IR_s}{R_{sh}} \tag{3}$$

Table 1 Comparison of diode-based model:

Factors	SDM	DDM	TDM
Complex	Low	Moderate	High
Accuracy	Low	Slightly Improved	High
Computational time	Low	Moderate	High
Parameters	Less	Slightly more	up to nine

Table 1 is the brief summary of classification of the diode model used in PV cell for the extraction of the output current. Above output current equation is the basic method for the estimation of energy generated from the PV cell. So the studies of these models are helpful for finding and developing the accurate model of PV cell.

3. Discussion on the proposed model by various researchers:

This literature review delves into the diverse modeling approaches employed to simulate and predict the performance of photovoltaic (PV) cells and systems, categorizing them into mathematical, analytical, and computational methods.

3.1. Models Based on the Mathematical Approach:

This segment explores models that leverage mathematical formulations to derive crucial PV parameters and predict output. A foundational approach involves extracting parameters from manufacturer datasheets and fitting them into established equations. Jakhrani et al. [3] proposed an analytical method using the Lambert W function for a closed-form solution of output current, while Roberts et al. [4] emphasized the importance of evaluating individual sub-models for accurate system simulations, identifying derating factors as a significant source of uncertainty. Hassan et al. [5] focused on modeling radiation components based on arbitrary panel orientation, highlighting the impact of shading and suboptimal angles on efficiency. Nascimento Jr. Et al. [6] introduced a technique for deriving a consistent parameter set across varying environmental conditions, enhancing accuracy in fault diagnosis. Studies by [7] focused on parameter determination from datasheet information and aggregating modules, while [8] analyzed the effects of environmental factors and resistances through simulations. Amusat et al. [9] utilized the Single Diode Model (SDM) and the Secant method, comparing predictions with manufacturer data. Research by M. N. Amroun et al. [10] compared various models for maximum power output under Standard Test Conditions (STC), and Cheddadi et al. [11] addressed the inadequacy of manufacturer data by proposing a numerical method for parameter extraction. Phillips-Brenes et al. [12] introduced an energy-based modeling and control strategy for Maximum Power Point Tracking (MPPT), and Hassan et al. [13] developed a user-friendly empirical formula based on datasheet curves. Finally, Mlazi et al. [1] proposed a numerical method to estimate SDM parameters using datasheet information and a modified Newton-Raphson method.

3.2. Models Based on the Analytical Approach:

This section examines models rooted in the fundamental physical and electrical equations of PV cells, emphasizing symbolic manipulation of equations. Dongue et al. [14] introduced an enhanced five-point model to address inaccuracies in simplified models. Waliullah et al. [15] improved Delisle's model by incorporating a Double Diode Model (DDM) and considering non-linear temperature effects. Khezzar et al. [16] enhanced the four-parameter model, and Zerhouni et al. [17] developed a model to find optimal power, current, and voltage. Bal et al. [29] Proposed a simplified model with low complexity for MPPT implementation. Miceli et al. [18] introduced a rational function-based model to avoid implicit exponential forms. Yadir et al. [19] developed a numerical method for extracting DDM parameters, and Bana et al. [20] compared SDM and DDM under varying insolation. Jadli et al. [21] combined an analytical model with simulated annealing for parameter estimation. Ali et al. [22] presented an analytical approach for the fifth equation of the SDM, and Boutana et al. [23] introduced a simplified explicit model based on three parameters. Elkholy et al. [24] proposed method using field measurements and non-linear least squares fitting. Patro et al. [25] proposed a hybrid method combining analytical techniques and social learning differential evolution. Teong et al. [26] derived explicit formulas for photo-generated and diode saturation currents. Tifidat et al. [27] utilized a seven-parameter DDM with a reduced forms approach. Al-Shahri et al. [28] introduced a mathematical model for simulating PV system behavior, and Cotfas et al. [30] presented a hybrid successive discretisation algorithm for parameter extraction. Ben hmamou et al. (2022) [31] developed an improved Single Diode Model (SDM) for PV panels, utilizing a hybrid analytical/numerical method for parameter estimation. Finally, Sabudin et al. [32] introduced a novel model using a delay differential equation for solar irradiance prediction.

3.3. Models Based on the Computational Approach:

This section focuses on models that employ numerical methods and algorithms to simulate PV system behavior. R Chenni et al. [33] provided an overview of PV cell modeling using MATLAB. Andrei et al. [34] developed a mathematical model using curve fitting, and Morcillo-Herrera et al. [2] presented a method for calculating energy generation using climate data. Li et al. [35] improved PV system performance using compound parabolic concentrators and a six-parameter model. Shongwe et al. [36] applied the Gauss-Seidel method for parameter extraction under STC. Franzitta et al. [37,38] proposed criteria for rating the usability and accuracy of SDM and DDM. Madi et al. [39] and Louzazni et al. [40] explored the application of bond graph methodology for PV generator modeling. Kumari P et al. [41] proposed an enhanced evolutionary computing algorithm for parameter extraction. Das et al. [42] reviewed PV power forecasting methods, and Bedoud et al. [43] implemented and evaluated the Perturb and Observe MPPT technique. Rasheed et al. [44]

presented algorithms for solving the non-linear equation of a PV cell, and Sarkar et al. [45] proposed a Lambert W function-aided Three Diode Model (TDM) approach. Soliman et al. [46] proposed an equilibrium optimizer algorithm for TDM parameter identification. Rasheed et al. [47] investigated bisection and secant methods for solving the non-linear electrical behavior of PV cells. Ali et al. [48] proposed uncertainty reduction strategies for renewable energy sources and system loads. Omer et al. [49] presented a comparative study of ensemble machine learning methods for PV applications. Finally, Santos et al. [50] reviewed parameters and setups for steady-state operating temperature models.

Table 2 Proposed models for the estimation of performance of PV

A.Q. Jakhrani et al., 2014	3	PV parameter determination	Analytical method with Lambert W	Closed-form solution for output current	Closed-form solution	Numerical calculation of output voltage	Evaluate model under rapidly changing	Yes	NR method	Yes	No	No	Analytical
J.J. Roberts et al., 2016	4	PV performance model assessment	Assessment of 20 PV performance	Best performing model with error metrics	Systematic examination of models	Uncertainty in derating factors	Reduce uncertainties in derating factors	Yes	N/A	No	No	Yes	Analytical
Q. Hassan et al., 2016	5	PV panel orientation modeling	Mathematical model for arbitrary	Impact of module angle on power	Improved accuracy in energy	Low efficiency due to shading	Long-term reliability analysis	Yes	N/A	No	No	Yes	Mathematical
Aguinaldo J. Nascimento Jr. et al., 2017	6	PV parameter estimation	Parameter estimation for DDM	Consistent parameter set across	Improved accuracy in fault diagnosis	Variable parameters lack physical	N/A	Yes	N/A	Yes	No	Yes	Mathematical
H.G. Navada et al., 2017	7	PV module model parameters	Model fitting at three I-V curve points	Basic step for power system analysis	Datasheet information used	Evaluate accuracy under rapid changes	Grid integration challenges	Yes	N/A	Yes	No	Yes	Mathematical

Author(s) & Year	H. Phillips-Brenes et al., 2022	F. Cheddadi et al., 2021	M. N. Amroun et al. , 2021	R.O. Amusat et al., 2019	C.Nituca et al., 2018	Author(s) & Year
Reference No.	12	11	10	9	8	Reference No.
Research Focus	MPPT modeling and control	PV panel parameter extraction	PV maximum power output	PV module prediction	PV cell parameter analysis	Research Focus
Key Contribution	Port-Hamiltonian framework	Numerical method for parameter	Comparative analysis of mathematical	SDM model with Secant method	Simulation of irradiation, temp, resistance	Key Contribution
Key Findings	Current sensorless control	Analysis of irradiance and temperature	Agreement with reference model	Model error comparison with manufacturer	Effects of varying parameters	Key Findings
Strengths	Simplicity of calculations	Improved PV generator modeling	Practical tool for PV system design	Models to determine field test conditions	Finite element thermal model	Strengths
Limitations/Gaps	Effects of temperature variation	Accuracy of DDM not tested	Accuracy at lower irradiance and temperatures	Individual effects of environmental	Uncertainty in model parameters	Limitations/Gaps
Areas for Future Research	Adaptive parameter identification	Analyze long-term reliability	Address accuracy at lower levels	Investigate more complex models	Quantify uncertainty	Areas for Future Research
Computational Approach Used?	Yes	Yes	Yes	Yes	Yes	Computational Approach Used?
Specific Computational Method/Softwar	N/A	Numerical method	N/A	Secant Method	Finite Element Method	Specific Computational Method/Softwar
Parameter Extraction Focus	No	Yes	No	No	Yes	Parameter Extraction Focus
MPPT Focus	Yes	No	No	No	No	MPPT Focus
Irradiance/Environmental Focus	Yes	Yes	Yes	Yes	Yes	Irradiance/Environmental Focus
Model Type	Mathematical	Mathematical	Mathematical	Mathematical	Mathematical	Model Type

F.Z. Zerhouni et al., 2014	Author(s) & Year	R. Khezzar et al., 2014	M. Waliullah et al., 2015	S. Bogning Dongue et al., 2013	N.J. Mlazi et al., 2024	O. Hassan et al., 2022
17	Reference No.	16	15	14	1	13
PV cell optimal parameters	Research Focus	PV cell model improvement	PVT collector efficiency	PV module electrical behavior	PV parameter estimation	PV module modeling
Mathematical model for climatic factors	Key Contribution	Modified four-parameter model	DDM and multivariate Newton's	Enhanced nonlinear five-point model	Modified Newton-Raphson method	Empirical mathematical formula
Approach to find optimal MPP	Key Findings	Equal or superior accuracy	Improved efficiency with PVT	Better representation of electrical	Faster than standard NR method	Competitive accuracy
Considers interactions between factors	Strengths	Simple model	Considers nonlinear temperature	Design tool for PV systems	Utilizes datasheet information	Simple and user-friendly
Accuracy outside experimental	Limitations/Gaps	Shunt resistance accuracy	Simplified solar radiation calculation	Sensitivity analysis lacking	Doesn't address shunt resistance	Accuracy under extreme conditions
Include other environmental factors	Areas for Future Research	Add computational analysis	More sophisticated radiation	Add computational analysis	Include shunt resistance analysis	Investigate under extreme conditions
Yes	Computational Approach Used?	Yes	Yes	Yes	Yes	No
N/A	Specific Computational Method/Softwar	N/A	Multivariate Newton's	N/A	Modified Newton-Raphson	N/A
Yes	Parameter Extraction Focus	Yes	Yes	Yes	Yes	No
No	MPPT Focus	No	Yes	No	No	No
Yes	Irradiance/Environmental Focus	Yes	Yes	Yes	No	Yes
Mathematical	Model Type	Analytical	Analytical	Analytical	Numerical	Empirical

M. Sqib Ali et al., 2020	U. Jadli et al., 2017	Author(s) & Year	S. Bana et al., 2016	S. Yadir et al., 2015	R. Miceli et al., 2015	Satarupa Bal et al., 2014
22	21	Reference No.	20	19	18	29
SDM analytical approach	PV parameter estimation	Research Focus	SDM and DDM comparison	PV cell parameter extraction	PV model with rational function	PV array simulation
Analytical approach for fifth equation	Analytical model with simulated	Key Contribution	Iterative technique for parameter	Numerical method for physical	Rational function model	Simplified mathematical model
Superior to SDM and DDM	PV characteristics align with real	Key Findings	DDM accurate under low insolation	Improved compatibility of I-V curves	Avoids implicit exponential forms	Low complexity and data storage
Uses MPP on P-I curve	Evaluated using multiple performance	Strengths	Calculates photo-generated current	Computationally efficient	Comparison with DDM	Accurately fits experimental curves
Effect of temperature variation	Computational complexity of simulated	Limitations/Gaps	Computational analysis needed	Computational complexity analysis	Performance under partial shading	Applicability to wider PV technologies
Discuss shunt resistance accuracy	Discuss computational complexity	Areas for Future Research	Discuss effect on MPPT	Test under varying conditions	Analyze dynamic behavior	Test wider range of PV technologies
Yes	Yes	Computational Approach Used?	Yes	Yes	Yes	Yes
N/A	Simulated annealing	Specific Computational Method/Softwar	Iterative technique	Iterative injection extraction	N/A	N/A
Yes	Yes	Parameter Extraction Focus	Yes	Yes	Yes	No
No	No	MPPT Focus	No	No	No	Yes
Yes	Yes	Irradiance/Environmental Focus	Yes	Yes	Yes	Yes
Analytical	Analytical	Model Type	Analytical	Analytical	Analytical	Analytical

O.A. Al-Shahri et al., 2020	K.Tifidat et al., 2020	K.L. Teong et al., 2021	Author(s) & Year	S.Kumar Patro et al., 2020	A.Elkholy et al., 2019	N. Boutana et al., 2017
28	27	26	Reference No.	25	24	23
PV system simulation	DDM parameter extraction	Five parameter PV model	Research Focus	Double diode PV model	PV module parameter	Simplified explicit PV
Improved mathematical model	Reduced forms approach	Explicit formulas for Iph and Io	Key Contribution	Hybrid analytical and social learning	Nonlinear least squares fitting	Mathematical equation with three parameters
Cell temp/irradiation dominant	Simplified parameter extraction, lower	Higher accuracy in I-V curve fitting	Key Findings	Lower error indices	Optimal parameter values	Superior accuracy and simplicity
Correlation analysis	High efficiency validated	Direct analytical derivation	Strengths	Useful under low irradiance and partial	Fast and simple method	Accurately predicts I-V characteristics
Lack of data preprocessing	Performance under complex	Steady state I-V curve focus,	Limitations/Gaps	Applicability to wider PV	Shunt resistance accuracy,	Model in large
Detailed data preprocessing	Evaluate performance under complex	Analyze ability to predict under dynamic	Areas for Future Research	Assess applicability to wider range,	Deeply discuss shunt resistance accuracy,	Analyze dynamic behavior
Yes	Yes	Yes	Computational Approach Used?	Yes	Yes	Yes
MATLAB	N/A	N/A	Specific Computational Method/Softwar	Social learning differential evolution	Excel solver	N/A
No	Yes	Yes	Parameter Extraction Focus	Yes	Yes	Yes
No	No	No	MPPT Focus	No	Yes	No
Yes	Yes	Yes	Irradiance/Environmental Focus	Yes	Yes	Yes
Mathematical	DDM	Five parameter model	Model Type	Double diode model	Five parameter model	Analytical

C.Morcillo-Herrera et al., 2014	H. Andrei et al., 2012	R. Chenni et al., 2007	S.N. Md Sabudin et al., 2024	Author(s) & Year	D. Ben hmamou et al., 2022	Cotfas et al., 2021
2	34	33	32	Reference No.	31	30
Energy generation calculation	PV cell performance	PV cell modeling	Solar irradiance prediction	Research Focus	Accurate PV panel model	Parameter extraction
Mathematical model and climate data	Curve fitting method	Comparison of PV models	DDE model	Key Contribution	SDM with ideal and non-ideal network	HDSA algorithm
Real efficiency lower than STC	Impact of cell connections	SDM/DDM parameter challenges	Accurate in decay phase	Key Findings	Lower computation time,	Improved RMSE
Tool for planning projects	LabVIEW and MATLAB validation	Foundational overview	Novel DDE use	Strengths	Analytical estimation based on datasheet,	Algorithm accuracy
Daily average data reliance	Steady-state focus	Lack of quantitative analysis	Deviation in growth phase	Limitations/Gaps	Steady-state I-V and P-V focus, Dynamic	Static I-V focus
Transient variations impact	Dynamic environmental evaluation	Advanced parameter extraction	Integration with control strategies	Areas for Future Research	Dynamic optimization for global MPP	Dynamic environmental evaluation
Yes	Yes	Yes	Yes	Computational Approach Used?	Yes	Yes
MATLAB	LabVIEW, MATLAB	MATLAB	MATLAB, Runge-Kutta, Nelder-Mead	Specific Computational Method/Softwar	Hybrid analytical/numerical	Custom Algorithm
No	No	Yes	No	Parameter Extraction Focus	Yes	Yes
No	No	No	No	MPPT Focus	Yes	No
Yes	Yes	No	Yes	Irradiance/Environmental Focus	Yes	No
Mathematical	Mathematical	Empirical, SDM, DDM	Mathematical	Model Type	SDM	N/A

Mohamed Louzazni et al., 2019	S.Madi et al., 2016	V. Franzitta et al., 2017	V. Franzitta et al., 2016	S.Shongwe et al., 2015	Author(s) & Year	W.Li et al., 2016
40	39	38	37	36	Reference No.	35
Dynamic PV modeling	PV generator modeling	DDM usability and accuracy	SDM usability and accuracy	PV module modeling	Research Focus	PV system performance with CPCs
Bond graph from SDM/DDM	Bond graph methodology	Comparison of simplified DDMs	Comparison of simplified SDMs	Gauss-Seidal method	Key Contribution	Six-parameter lumped model
Simulation results demonstrate	99.41% accuracy	Model selection criteria	Model selection criteria	Parameter extraction under STC	Key Findings	Ideality factor, current dominant
Dynamic modeling approach	Systematic model derivation	Detailed procedures	Detailed procedures	Algorithm provided	Strengths	Optimized parameter extraction
MPPT integration discussion	MPPT integration discussion	Steady-state focus	Steady-state focus	Sensitivity analysis lacking	Limitations/Gap s	Manufacturing tolerances impact
Comparative accuracy analysis	Applicability across PV technologies	Detailed computational analysis	Detailed computational analysis	Detailed computational analysis	Areas for Future Research	Detailed computational analysis
Yes	Yes	Yes	Yes	Yes	Computational Approach Used?	Yes
N/A	MATLAB SIMULINK	N/A	N/A	MATLAB	Specific Computational Method/Softwar	ANSYS CFX, MATLAB
No	No	Yes	Yes	Yes	Parameter Extraction Focus	Yes
No	No	No	No	No	MPPT Focus	No
Yes	Yes	No	No	Yes	Irradiance/Envir onmental Focus	No
Bond Graph	Bond Graph	DDM	SDM	SDM	Model Type	Mathematical

Author(s) & Year	D.Sarkar et al., 2021	M. Rasheed et al., 2021	K. Bedoud et al., 2019	U.K. Das et al., 2018	Ashwini Kumari P et al., 2017	Author(s) & Year
Reference No.	45	44	43	42	41	Reference No.
Research Focus	BIPV module modeling	PV cell equation solving	MPPT technique evaluation	PV power forecasting	PV parameter extraction	Research Focus
Key Contribution	Lambert W function aided TDM	Newton-Horner algorithm	P&O algorithm	Review of forecasting methods	Enhanced AGA	Key Contribution
Key Findings	Low average error	Improved accuracy	High performance under varying	ANN/SVM performance	Improved curve fitting	Key Findings
Strengths	Robust and effective	Iterative approach	Fast performance	Comprehensive review	Multi-objective optimization	Strengths
Limitations/Gaps	Sensitivity analysis lacking	Broader comparison lacking	Comparative analysis lacking	Long-term forecasting improvement	Applicability across PV technologies	Limitations/Gaps
Areas for Future Research	Thermal performance impact	Convergence rate analysis	Performance under rapid changes	Model efficiency optimization	Yes	Areas for Future Research
Computational Approach Used?	Yes	Yes	Yes	Yes	Custom Algorithm	Computational Approach Used?
Specific Computational Method/Softwar	MATLAB	MATLAB	MATLAB/SIMULINK	ANN, SVM, GA	Yes	Specific Computational Method/Softwar
Parameter Extraction Focus	Yes	Yes	No	No	No	Parameter Extraction Focus
MPPT Focus	No	No	Yes	No	Yes	MPPT Focus
Irradiance/Environmental Focus	Yes	No	Yes	Yes	Evolutionary Algorithm	Irradiance/Environmental Focus
Model Type	TDM	Numerical	MPPT Algorithm	Statistical, Machine		Model Type

Author(s) & Year	Santos et al., 2022	Z.M. Omer et al., 2022	Eman S. Ali et al., 2022	M. Rasheed et al., 2021	M.A. Soliman et al., 2021
Reference No.	50	49	48	47	46
Research Focus	PV operating temperature models	PV EML method comparison	RES uncertainty modeling	PV cell equation solving	PV TDM parameter identification
Key Contribution	Review of parameters	CatBoost, Random Forest, etc.	Uncertainty reduction strategies	Secant method	Equilibrium optimizer algorithm
Key Findings	Significant parameters highlighted	CatBoost best performance	99% reduction in uncertainty	Lower iteration count	Low error
Strengths	Algorithm development aid	Comparative study	Effectiveness demonstrated	Numerical comparison	Physics-based algorithm
Limitations/Gaps	Dynamic models needed	Computational complexity analysis	Temporal correlation lacking	Broader comparison lacking	Computational complexity analysis
Areas for Future Research	Advanced measurement techniques	Wider climatic zone testing	Integration with real-time control	Real-time implementation analysis	Performance under rapid changes
Computational Approach Used?	N/A	Yes	Yes	Yes	Yes
Specific Computational Method/Softwar	N/A	MATLAB	N/A	MATLAB	MATLAB
Parameter Extraction Focus	No	Yes	No	Yes	Yes
MPPT Focus	No	Yes	No	No	No
Irradiance/Environmental Focus	Yes	Yes	Yes	No	Yes
Model Type	Review	Machine Learning	N/A	Numerical	TDM

4. Analysis and Discussion

This review has explored a diverse landscape of PV performance models, categorized into mathematical, analytical, and computational approaches. Each category offers unique strengths and addresses specific challenges in accurately simulating PV system behavior.

Mathematical Models: Balancing Simplicity and Accuracy

Mathematical models, often the foundational step in PV analysis, offer a balance between simplicity and accuracy. The work of Jakhrani et al. [3] exemplifies this, providing closed-form solutions for crucial parameters using the Lambert W function. However, these models often rely on simplifying assumptions, potentially limiting their accuracy under complex environmental conditions.

Roberts et al. [4] highlighted the importance of evaluating sub-models and addressing uncertainties in derating factors, emphasizing the need for robust models that can accurately predict performance under real-world scenarios. Hassan et al. [5] further underscored this point by demonstrating the significant impact of panel orientation and environmental factors on energy generation.

Nascimento Jr. et al. [6] and Cheddadi et al. [11] addressed the challenge of parameter consistency across varying environmental conditions, aiming to derive a single, reliable parameter set. These models enhance accuracy in fault diagnosis and predictive maintenance, addressing the limitations of manufacturer-provided data. However, many models within this category are based on the SDM, and further validation with the more complex DDM is necessary.

Recent mathematical models, such as those by Phillips-Brenes et al. [12], Hassan et al. [13], and Mlazi et al. [1], focused on simplifying parameter extraction and enhancing model accuracy. These models offer practical tools for PV system design and analysis, but further research is needed to evaluate their performance under extreme environmental conditions and to fully quantify uncertainties.

Analytical Models: Inquiring into Physical Phenomena

Analytical models, rooted in fundamental physical and electrical equations, provide deeper insights into PV cell behavior. Dongue et al. [14] and Waliullah et al. [15] demonstrated the benefits of incorporating DDM and nonlinear effects to enhance model accuracy, particularly under varying temperature and irradiance conditions.

Khezzar et al. [16] and Zerhouni et al. [17] focused on improving the accuracy of four-parameter models by refining open-circuit voltage equations and developing formulas that consider climatic factors. These models offer simplicity and accuracy but may not fully account for complex environmental interactions.

Bal et al.[29] and Miceli et al. [18] emphasized the need for simplified and robust models for effective MPPT algorithm implementation, highlighting the trade-off between model complexity and computational efficiency. Yadir et al. [19] and Bana et al. [20] compared SDM and DDM, demonstrating that DDM is more suitable for describing physical phenomena, particularly under low insolation.

Recent analytical models, such as those by Teong et al. [26] and Tifidat et al. [27], focused on deriving explicit formulas and simplifying parameter extraction processes. These models offer improved accuracy and efficiency, but further research is needed to assess their applicability across a wider range of PV technologies and under complex conditions.

Computational Models: Exploring Advanced Algorithms and Data

Computational models, utilizing numerical methods and algorithms, provide powerful tools for simulating PV system behavior. R.Chenni et al. [33] provided a foundational overview of PV cell modeling using MATLAB, comparing empirical, SDM, and DDM models. Andrei et al. [34] and Morcillo-Herrera et al. [2]

demonstrated the use of LabVIEW and MATLAB for validating theoretical methods and calculating energy generation.

Li et al. [35] developed a six-parameter model incorporating CPC gain coefficients, while Shongwe et al. [36] presented a step-by-step application of the Gauss-Seidel method for parameter extraction. Franzitta et al. [37,38] proposed criteria for rating the usability and accuracy of SDM and DDM, emphasizing the importance of balancing accuracy and complexity.

Madi et al. [39] and Louzazni et al. [40] explored the application of bond graph methodology for dynamic modeling, offering a unified representation of energy flow. Kumari P et al. [41] proposed an enhanced evolutionary computing algorithm (AGA) for multi-objective optimization, aiming to improve curve fitting and alleviate computational complexity.

Recent studies by Sarkar et al. [45], Soliman et al. [46], and Rasheed et al. [47] focused on solving non-linear equations using advanced numerical methods and optimization algorithms, such as the Lambert W function and equilibrium optimizer algorithm (EOA). These models offer improved accuracy and robustness but require further analysis of computational complexity and real-time applicability.

Omer et al. [49] demonstrated the effectiveness of Ensemble Machine Learning (EML) methods, particularly CatBoost, for PV applications, highlighting the potential of data-driven approaches. Santos et al. [50] reviewed significant parameters and experimental setups for accurate temperature models, emphasizing the need for dynamic models that capture transient behavior.

The "better" model depends on the specific application and requirements.

- For research and development, where detailed physical insights are crucial, advanced analytical models incorporating DDM and sophisticated parameter extraction techniques are preferable.
- For real-time monitoring, forecasting, and control applications, where adaptability and robustness are paramount, computational models leveraging machine learning and optimization algorithms excel.
- For preliminary design and feasibility studies, where quick and reasonably accurate estimations are needed, mathematical models with closed-form solutions are advantageous.

Benefits of Improved PV Performance Models:

- Enhanced System Design and Optimization: Accurate models enable precise prediction of PV system performance, facilitating optimal design and configuration for maximum energy yield.
- Improved MPPT Algorithm Performance: Robust models provide accurate I-V characteristics, enabling the development of more efficient MPPT algorithms that maximize power extraction under varying conditions.
- Accurate Forecasting and Grid Integration: Reliable models are crucial for accurate PV power forecasting, facilitating seamless grid integration and energy management.
- Enhanced Fault Diagnosis and Predictive Maintenance: Advanced models enable early detection of faults and degradation, facilitating proactive maintenance and extending the lifespan of PV systems.
- Reduced Uncertainty and Improved Investment Decisions: Accurate models reduce uncertainties in PV system performance, providing greater confidence for investors and stakeholders.

Overall Analysis:

The trend is moving towards more sophisticated modeling techniques, with a clear emphasis on incorporating dynamic environmental conditions and employing advanced computational methods. The rise of machine learning and optimization algorithms has significantly enhanced the accuracy and adaptability of PV performance models.

However, several areas require further research:

- Validation of models under diverse and extreme environmental conditions.
- Development of dynamic models that capture transient behavior.
- Quantification of uncertainties associated with model parameters and predictions.
- Integration of models with real-time control and operational strategies.
- Analysis of the computational complexity and real-time feasibility of advanced models.
- Increased focus on shunt resistance and its effects, especially under low irradiance.

By addressing these gaps, researchers can develop more robust and reliable PV performance models, accelerating the adoption of solar energy and contributing to a sustainable energy future.

5. Conclusion

This comprehensive review has systematically examined the evolution and diversity of photovoltaic (PV) performance modeling approaches, encompassing mathematical, analytical, and computational methodologies. The analysis underscores the critical role of accurate PV modeling in optimizing system design, enhancing maximum power point tracking (MPPT) efficiency, facilitating reliable forecasting, and enabling proactive maintenance.

Mathematical models, while offering simplicity and closed-form solutions, often rely on simplifying assumptions that may limit their accuracy under complex environmental conditions. Analytical models, grounded in fundamental physical principles, provide deeper insights into PV cell behavior, particularly through the incorporation of double diode models (DDMs) and the consideration of nonlinear effects. Computational models, leveraging advanced numerical methods and machine learning algorithms, demonstrate superior adaptability and robustness, particularly in real-time applications.

The selection of an optimal modeling approach is contingent upon the specific application requirements, balancing factors such as accuracy, computational efficiency, and the need for detailed physical insights. The trend towards incorporating dynamic environmental factors and employing advanced computational techniques, such as machine learning and optimization algorithms, highlights the increasing sophistication of PV performance modeling.

However, several research gaps remain, including the validation of models under extreme environmental conditions, the development of dynamic models capturing transient behavior, the quantification of uncertainties, and the integration of models with real-time control strategies. Future research efforts should prioritize addressing these gaps to develop more robust and reliable PV performance models. Specifically, increased focus on shunt resistance modeling, particularly under low irradiance conditions, and the analysis of computational complexity for real-time applications are warranted.

By advancing PV performance modeling, researchers can contribute to the accelerated adoption of solar energy, thereby promoting a sustainable and resilient energy future. The development of hybrid models that integrate the strengths of mathematical, analytical, and computational approaches holds significant promise for achieving enhanced accuracy and reliability in PV system performance prediction.

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