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Research paper

Extracting photovoltaic cells parameters for three diode model using HSDA algorithm

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ABSTRACT

Developing the metaheuristic algorithms directly for extracting the photovoltaic cells and panels (PV) parameters or the implementation of algorithms for PV already used for other problems conduct to accurately obtain parameters and, generally, in a short time. The objective of the paper is to accurately extract the parameters of the photovoltaic cells and panels. To obtain this the hybrid successive discretization algorithm (HSDA) is applied to the triple diode model (TDM) for the extraction of photovoltaic cells and panels parameters. Using HSDA, nine parameters are extracted for two photovoltaic cells and four photovoltaic panels. The HSDA algorithm results for root mean square errors (RMSE) and mean absolute errors (MAE) are compared with other ones obtained with the best algorithms from research literature for prove the performance of the algorithm considered. The comparison proves that the HSDA algorithm has lower or equal RMSE. Therefore, the decrease in RMSE varies from 0.4 % to 38.5 %, in the case of the RTC France silicon photovoltaic cell (La Radiotechnique Compele) and for the Photowatt - PWP201 photovoltaic panel the variation is from 0.01 % to 813 %. The RMSE for STM6–40 is around 4 times lower. The root mean square error decreases 4 times for Kyocera KC200GT and for PVM 752 GaAs the decrease varies between 33 % and 6 times. The comparison between the models used for photovoltaic cells shows that the TDM has given lower values for RMSE and MAE proving it is the best solution to analyze them.

1. Introduction

The European Commission (EC) established in 2018 the target for renewable energy of 32 % and to this purpose the EC also set some rules (Anon, 2024a). The European Green Deal program was launched and together with the political situation, and the energetic security problems, lead to a new target, 45 % for renewable energy until 2030 (Anon, 2024b). Romania is part of this action and in the last several years, but especially, in the last two years the investments in photovoltaic systems have grown exponentially through Photovoltaic Green House (Anon, 2024c). The owners of the houses are becoming prosumers.

Solar energy which is converted into electrical energy using PV modules becomes the most important player in renewable energy. In 2017 electric and thermal energy obtained from solar energy was almost two times more than wind energy and it will reach 69 % from renewable energy in 2050 (Sawin et al., 2017). In accordance with the DVN report (from Det Norske Veritas Holding AS), the electric energy produced by the photovoltaic systems is already one the cheapest from the new types. It will cover 38 % from the electric energy produced in 2050 (Anon, 2024d).

The forecast of the photovoltaic power generation is very important for the owner of photovoltaic farms and for the national electrical systems because photovoltaic systems begin to take an important market share. In this context, the extraction of the photovoltaic modules parameters has to be accurate. To develop high-efficiency cells, it is essential to accurately calculate both internal and external parameters. This provides researchers with the opportunity to identify solutions for modifying these parameters in order to enhance the performance of photovoltaic cells. The most effective solution for accurate extraction of the parameters was found to be utilizing metaheuristic algorithms applied to one of the models for the photovoltaic cells and panels. One diode model (SDM) comes with five parameters which are taken into account, three appearing in all three models, such as photogenerated current I_{ph}, series resistance R_s and shunt resistance R_{sh} and the other two specific for each model, such as reverse saturation current I_o and ideality factor series of diode n (Cotfas et al., 2021). In the case of the two diode model (DDM) I_o and n are duplicated, and in the case of the TDM model, these are triplicated.

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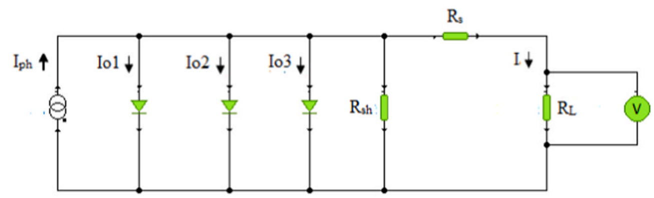


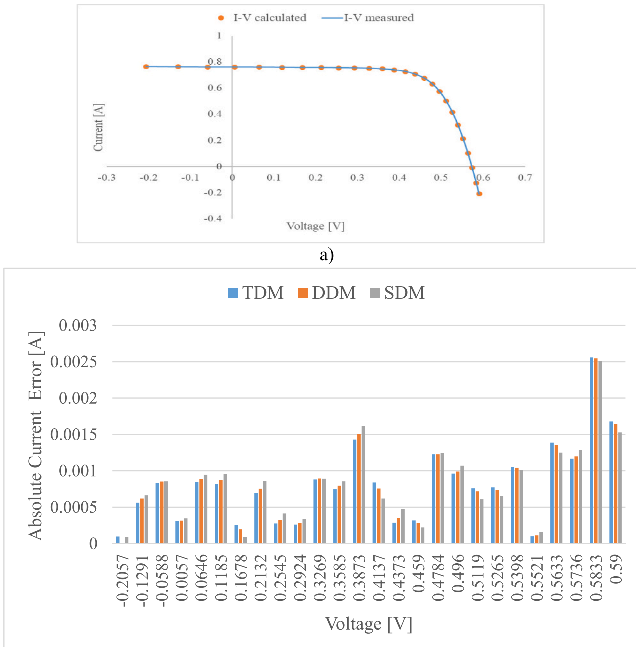
Fig. 1. Equivalent circuit of photovoltaic cells with three diode –TDM model.

There are a lot of analytical methods and algorithms published in the specialized literature that extract the photovoltaic cells parameters using SDM model (Bakir, 2023) and DDM model (Gnetchejo et al., 2021; Younis et al., 2022), but few use TDM model due to the high number of parameters that must be determined. The TDM model is essential because it takes into account all mechanisms of photovoltaic cells, leading to highly accurate calculations of all nine parameters. This enables researchers from chemistry, physics, material science, and the manufacturers to improve the performance of PVs.

Khanna et al. used the Particle Swarm Optimization algorithm (PSO) to estimate the nine parameters of the silicon photovoltaic cell with 154.8 cm^2 using the TDM model. The series resistance is considered as a linear function of the current. The mean absolute error (MAE) is used to compare the performance of the DDM model with TDM model. In most cases considered the MAE is slightly higher for TDM than DDM model (Khanna et al., 2015). The gradient-based optimizer algorithm (GBO) is based on population method. It has two stages: locale escaping operator and gradient search rule. The control of the direction of the agent search is based on the Newton method (Ismaeel et al., 2021). The GBO algorithm was applied to extract the parameters of the RTC photovoltaic cell using all three models. In the case of RMSE, the results are comparable with others from the specialized literature. RMSE for the SDM model is 9.8602E-4, for DDM it is 9.8252E-4, and for TDM it is 9.8250E-4. Marine predators algorithm (MPA) is used to extract nine parameters of RTC photovoltaic cell, STM6–40 and PVM 752 GaAs photovoltaic panels. It is part of the biology algorithms and has three periods called high-speed fraction where the predator is lower than the prey, unity speed fraction where the speed is equal and low-speed fraction where the prey is lower than the predator (Rezk and Abdelkareem, 2022). In the case of the PVM 752 GaAs, MPA is applied for DDM and TDM models. The TDM model has a lower RMSE compared to the DDM model, indicating that the TDM model should be used to determine photovoltaic cell parameters. Abdel-Basset et al. proposed improved generalized normal distribution algorithm (RGNDO) to extract the nine parameters of RCT France photovoltaic cell, Kyocera KC200GT, Ultra 85-P and STP 6–120 photovoltaic panels (Abdel-Basset et al., 2021). The RGNDO is obtained by adding a method to accelerate convergence for the generalized normal distribution algorithm. The method is called the ranking-based updating method. The algorithm is applied only for TDM model. Li et al.l adopt a new strategy to calculate the PV parameters called data prediction–based meta-heuristic algorithm (DPMhA) based on machine learning. An extreme learning machine (ELM) is used in this algorithm. DPMhA is applied to calculate the parameters of the RTC photovoltaic cell for SDM, DDM and TDM models (Li et al., 2021). Only the root mean square error (RMSE) is used in comparison process with other algorithms. TDM model has a lower RMSE compared to the SDM and DDM models. The tree growth algorithm (TGA) is used to accurately extract the parameters for the PV for all three models. It is a nature inspired algorithm, with two stages. The first one is called intensification, where the trees movement is towards better food. The second one is diversification where other trees go to the virgin places. The method assures a balance between the two stages (Diab et al., 2020a) through parameters adjusting. Improved gray wolf optimizer (IGWO) is an improved version of the gray wolf optimizer algorithm. The improved version reduces the probability that the algorithm finds a local minimum and ensures the optimum balance between the exploration and exploitation process. The

Table 1
Nine parameters extracted for RTC, RMSE and MAE.

Algorithm	I_{ph} [A]	I_{o1} [µA]	I_{o2} [µA]	I_{o3} [µA]	n_1	n_2	n_3	R_s [Ω]	R_{sh} [Ω]	RMSE [E-04]	MAE [E-04]	Rank
HSDA TDM	**0.76078794**	**0.23184466**	**3.11308223**	**0.0884997**	**1.45130774**	**2.48306475**	**2.0596537**	**0.03686774**	**57.04873692**	**9.7693**	**8.11641**	**1**
HSDA DDM	0.7607941	0.2267032	0.8267308	-	1.451	2.0303627	-	0.0367628	55.39838576	9.8602	8.16746	-
HSDA SDM	0.7607758	0.3244462	-	-	1.4811823	-	-	0.0363770	53.71452088	9.8602	8.27989	-
OBEDO	0.7608	0.588	0.234	0.979	1.9995	1.4537	2.7316	0.0367	55.7780	9.8082	8.13989	2
MIGTO	0.760781	0.225974	0.239880	0.509466	1.4510168	1.9999999	1.9959999	0.0367404	55.485437	9.8248	8.18489	3
STF	0.7607810	0.22597	0.072348	0.677	1.4510167	2	2	0.0367404	55.4854309	9.8248	8.18512	3
GBO	0.76077553	0.78129	0.221556	0.00721	1.99999453	1.44938484	1.975652	0.0367583	55.62330625	9.82503	8.18589	4
CLSHADE	0.76076	0.87650	0.2044	0.000180	1.99500	1.44240	1.89000	0.036920	55.68000	9.840147	8.13626	5
COA	0.7608824	0.2094596	0.1914271	0.237428	1.75399957	1.43961703	1.9	0.036921	53	9.907123	8.27532	6
MPA	0.761	0.005946	0.1835	220.17	1.4308	1.43074	5	0.037754	79.310199998	9.9372	7.64459	7
RGNDO	0.760500	0.0908	1.96	0.158	1.3766	2	2	0.0380	61.3221	10.42701	8.34977	8
TGA	0.7611	0.30477	0.25571	0.32399	1.9999	1.4623	2	0.0363	51.14	10.5655	8.60143	9
STLBO	0.7608	0.2349	0.2297	0.4443	1.4541	2	2	0.0367	55.2641	11.23061	7.87947	10
FC-EPSO3	0.76079	0.16786	0.91978	0.25879	1.4257	1.9949	2	0.037215	55.742	11.49272	8.06008	11
IGWO	0.7607	0.227	0.314	0.234	1.9256	1.9600	1.4500	0.0367	54.888	15.6825	89.4669	12
OBWOA	0.76077	0.2353	0.2213	0.4573	1.4543	2	2	0.03668	55.4448	15.89261	10.7225	13



a)

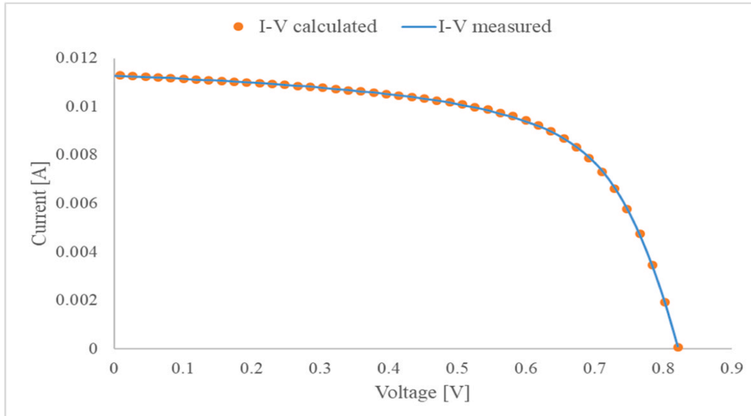
b)

Fig. 2. RTC France photovoltaic cell: a) Comparison between I-V characteristics measured and calculated using HSDA algorithm for TDM model; b) Absolute current errors for HSDA algorithm in the cases TDM, DDM, and SDM models.

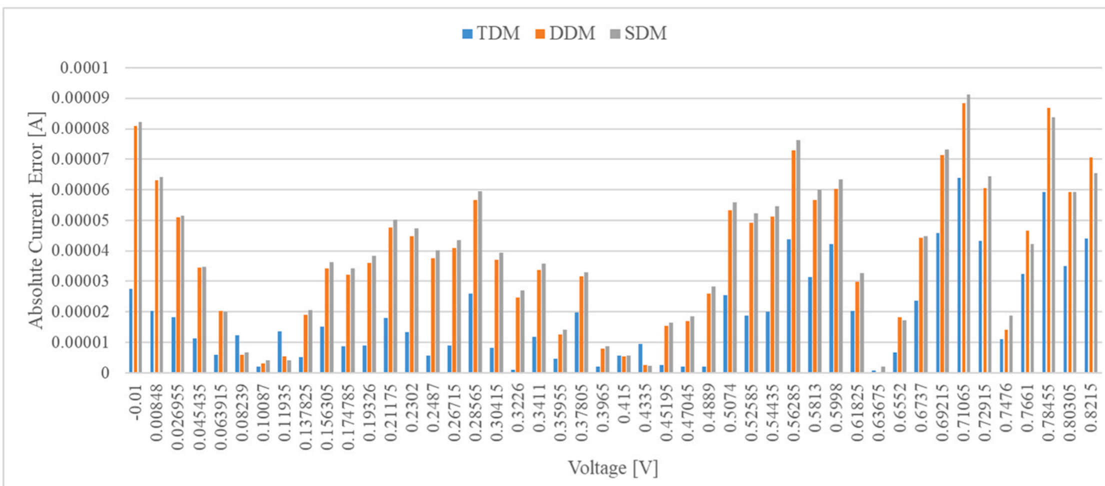
IGWO is used to estimate the nine parameters of RCT France photovoltaic cell and Photowatt-PWP201 photovoltaic panel (Ramadan et al., 2021). Qais et al. used Circle Search Algorithm (CSA) to identify the nine parameters of the CS6K-280 M, KC200GT, and MSX-60 photovoltaic panels. It is a population based algorithm and uses the property from geometry where the radius is perpendicular to the tangent in the tangent point (Qais et al., 2022). The algorithm is applied only for the TDM model without comparison with the other two models. The parameters of two photovoltaic panels, PVM 752GaAs thin film and SQ 70, are extracted using TDM model by the Supply-Demand-Based Optimization Algorithm (SDOA). It is based on obtaining the balance between quality and price in the supply and demand economic process. It is easy to be implemented and has powerful optimization capabilities (Shaheen et al., 2022). Calasan et al. developed a novel iterative method based on the Lambert W function, CLSHADE (Ćalasan et al., 2021a). It is used to calculate the parameters for RCT photovoltaic cell and MSX-60 photovoltaic panel, in the case of the DDM and TDM models. In this paper, 92 methods and algorithms are presented for extracting the parameters of the RTC France photovoltaic cell using the double diode model. Diab et al. have applied coyote optimization algorithm (COA) to extract the parameters of the RTC France photovoltaic cell using all three models, SDM, DDM, and TDM. This algorithm is simple to implement because it uses only two parameters for control. It has good tracking characteristics and offers a good balance for the exploration and exploitation phases (Diab et al., 2020b). TDM model has a lower RMSE compared to the SDM and DDM models. Elaziz et al. have improved the whale optimization algorithm using the opposition-based learning, OBWOA. The exploration of the search space was improved by using this method. If the WOA algorithm can fall in a local optimum, through added OBL, the best solution can be obtained by searching in forward and backward directions, enhancing the convergence, and reducing the computing time (Elaziz and Oliva, 2018). The OBWOA algorithm is used for all three models. A hybrid metaheuristic algorithm is proposed to enhance the accuracy of the Ensemble particle swarm optimizer algorithm by using the fractional chaos maps FC-EPSO (Yousri et al., 2020). Kullampalayam et al. proposed a new algorithm called leveraging the opposition-based

Table 2
Nine parameters extracted for aSi, RMSE and MAE.

Algorithm	I_{ph} [A]	I_{o1} [μA]	I_{o2} [μA]	I_{o3} [μA]	n_1	n_2	n_3	R_s [Ω]	R_{sh} [Ω]	RMSE [E-05]	MAE [E-05]	Rank
HSDA TDM	**0.01133067**	**90.5914527**	**10.8816527**	**0.0123991**	**9.99938271**	**10**	**2.3874133**	**2.24712579**	**1108.3322476**	**2.4439838**	**1.86515**	**1**
HSDA DDM	0.01134914	0.22670320	1.06053042	-	3.07946212	4.09911521	-	0.19879385	528.10082632	4.497351	3.82863	2
HSDA SDM	0.011347	0.7047542	-	-	3.353834	-	-	0.040283	520.065069	4.619456	3.96462	3



a)



b)

Fig. 3. aSi photovoltaic cell: a) Comparison between I-V characteristics measured and calculated using HSDA algorithm for TDM model; b) Absolute current errors for HSDA algorithm in the cases TDM, DDM, and SDM models.

exponential distribution optimizer (OBEDO). It is applied to extract the parameters using all three models for five photovoltaic cells and modules. RMSE calculated using OBEDO algorithm is 9.8602E-4 for the SDM model, 9.8250E-4 for DDM model, and 9.8082E-4 for TDM (Kullampalayam Murugaiyan et al., 2024). The TDM model once again demonstrates its superiority in accurately extracting parameters. Abdel-Basset et al. applied the memory-based improved gorilla troops optimizer (MIGTO) to calculate the parameters for RTC photovoltaic cell and for four panels. TDM is applied only for RTC (Abdel-Basset et al., 2022). Gao et al. utilized the special trans function (STF) to enhance parameter extraction performance, as it is more accurate than the Lambert W (Gao et al., 2024). The algorithm is applied for DDM and TDM models with very good results for RMSE and convergence speed. Shaheen et al. implemented the Enhanced artificial gorilla troops algorithm (EAGT) (Shaheen et al., 2023) and used the Enhanced Marine Predators Optimizer(EMPO) (Elsayed et al., 2021) for the following photovoltaic modules KC200GT PV, STM6–40/36 PV and SP70. The algorithms are applied only for the TDM model.

The SDM and DDM models are utilized by over 100 methods and algorithms (Ćalasan et al., 2021b), whereas the TDM model is used by a smaller number. The main goal of the paper is to implement and use the hybrid successive discretization algorithm for the TDM model and prove its capabilities in comparison with the other algorithms from the specialized literature and SDM and DDM models, and to increase the accuracy in parameter extraction using a very small iterations number. Thus, a tool with high accuracy is provided to researchers and manufacturers of photovoltaic cells and panels.

The novelty and the major contributions of the paper consist of:

- implementing and using for the first time the HSDA to determine the nine parameters using the TDM model for RTC France and amorphous silicon, aSi, photovoltaic cells and PWP201, STM6–40, Kyocera KC200GT and PVM 752 GaAs photovoltaic panels to extract nine parameters (TDM).
- two statistical tests, MAE and RMSE, are used to analyze the performance of the HSDA algorithm for extraction of the nine PV parameters.
- the calculated PV parameters considered using HSDA algorithm for TDM model are compared with ones obtained using SDM and DDM models, and the results for RMSE and MAE show for all cases considered an improvement in RMSE and MAE, in some cases around two times. In the case of RMSE, the improvements of the TDM model in comparison with SDM and DDM models are: 0.9 % for both models of the RTC cell, 89 % for SDM and 84 % for DDM of the aSi, 0.002 %

Table 3
Nine parameters extracted for PWP201, RMSE and MAE.

Algorithm	I_{ph} [A]	I_{o1} [μA]	I_{o2} [μA]	I_{o3} [μA]	n_1	n_2	n_3	R_s [Ω]	R_{sh} [Ω]	RMSE [E-03]	MAE [E-03]	Rank
HSDA TDM	**1.03051098**	**3.48227582**	**2.03E−12**	**2.2E−12**	**48.6428343**	**72.7146688**	**72.478122**	**1.20127834**	**982.37366036**	**2.425075**	**1.95607**	**1**
HSDA DDM	1.03227080	2.51196629	1.00838351	-	47.422967	47.7321215	-	1.23493750	737.2796796	2.587754	2.14548	-
HSDA SDM	1.0305143	0.34822630	-	-	48.642835	-	-	0.040283	981.9822803	2.425077	1.95695	-
STF	1.0305143	0.34823	2.0908E−12	2.219E−12	48.6428343	71.9998525	71.999999	1.20127102	981.982025	2.425082	1.95667	2
OBEDO	1.0305	1.43E−7	2.21E−9	0.348	46.764	49.728	48.642	1.2013	982.49	2.4251	1.95670	3
MIGTO	1.0305	0.346	0.00E+00	0.00E+0	48.643	49.768	36	1.2013	981.98	2.4251	1.95671	4
GBO	1.0305	0.000371	3.48	2.02E−7	48.4845	48.6435	49.9864	1.2012	982.1077	2.458311	2.05431	5
OBLWOA	1.0316	0	4.83	0	25.4792	49.9424	19.4348	1.1599	1000	2.759638	2.28459	6
WOA	1.0316	0	0	4.90	49.9999	49.9999	49.9999	1.1579	999.9977	2.777848	2.25036	7
TGA	1.0265	9.1105	0.020908	0.02325	47.422967	47.7321215	55.3284	1.0872	6201.9	3.72591	2.98071	8
CCNMGBO	1.0305	3.48	0.00000327	0.0594	48.6433	47.9312	49.9992	1.2013	982.0998	7.021456	5.3913	9
IGWO	1.03050884	1.25	0.777	1.54	49.2667226	48.3842266	48.255933	1.19868377	986.3365886	19.74519	13.5606	10
COA	1.032744	5.08919E−5	2.0923E−12	1.090E−12	720	46.7803483	72	1.256384	700	-	-	11

for SDM and 6.7 % for DDM of the PWP201, 2.4 % for SDM and 1.9 % for DDM of the STM6–40, 55.8 % for SDM and 0.6 % for DDM of the Kyocera KC200GT, 107 % for SDM and 88 % for DDM of the PVM_752GaAs

- To prove the superiority of the HSDA algorithm in extraction of the PV parameters the results are compared with ones obtained by the algorithms from research literature. The greatest improvement for RMSE varies between 0.4 % and 62.7 % for RTC, 0.003 % and almost three times for PWP201, 0.4 % and 62.7 % for RTC, 0.0012 % and almost five times for STM6–40, three and almost four times for Kyocera KC200GT, 32 % and six times for PVM_752GaAs in comparison with results for RMSE obtained by the other algorithms.

The three remaining parts of the paper are the following: the second section briefly presents the photovoltaic models for the cell and panel; the HSDA algorithm for triple diode model is described in the third section; the extracted parameters using the HSDA algorithm and the comparison with the ones obtained using other algorithms are presented and analyzed, for RTC France and aSi photovoltaic cell, and for PWP201, STM6–40, Kyocera KC200GT and PVM 752 GaAs photovoltaic panels in the fourth section; the conclusions and future works are presented in the last section.

2. PV models

Two regimes are used to characterize the photovoltaic cells and panels. One is the dynamic regime (Cotfas et al., 2016) and the most commonly used is the static regime (Cotfas et al., 2021). The current voltage, I-V, characteristic is analyzed using equivalent circuits in static regime and the mathematical models.

The mathematical model used underwent an evolution from the ideal one to the triple diode model which is the advanced one because all mechanisms are considered. The most commonly used was the one diode model with parasitic resistances which is described by Eq.1.

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

where $V_T = kT/q$ is the thermal voltage, k represents the Boltzmann constant, q is the elementary electrical charge and T represents the photovoltaic cell temperature. In the case of photovoltaic panel with N_s photovoltaic cells connected in series the mathematical model for one diode is described in Eq.2, (Sarjila et al., 2016).

$$I = I_{ph} - I_o\left(e^{\frac{V+N_sIR_s}{nN_sV_T}} - 1\right) - \frac{V + N_sIR_s}{N_sR_{sh}} \tag{2}$$

The triple diode model, which considers all mechanisms, such as diffusion - in the depletion layer described by the first exponential term, generation – recombination mechanism - in the junction's space charge area, defined by the second exponential term, and thermionic process with recombination in the defect area described by the third exponential term, is presented by Eq.3, and the equivalent circuit in Fig. 1.

$$I = I_{ph} - I_{o1}\left(e^{\frac{V+IR_s}{n_1V_T}} - 1\right) - I_{o2}\left(e^{\frac{V+IR_s}{n_2V_T}} - 1\right) - I_{o3}\left(e^{\frac{V+IR_s}{n_3V_T}} - 1\right) - \frac{V + IR_s}{R_{sh}} \tag{3}$$

where I_{o1}, I_{o2} and I_{o3} are the reverse saturation current for all three mechanisms, n_1, n_2 and n_3 are the ideality factors of diode for the mechanisms.

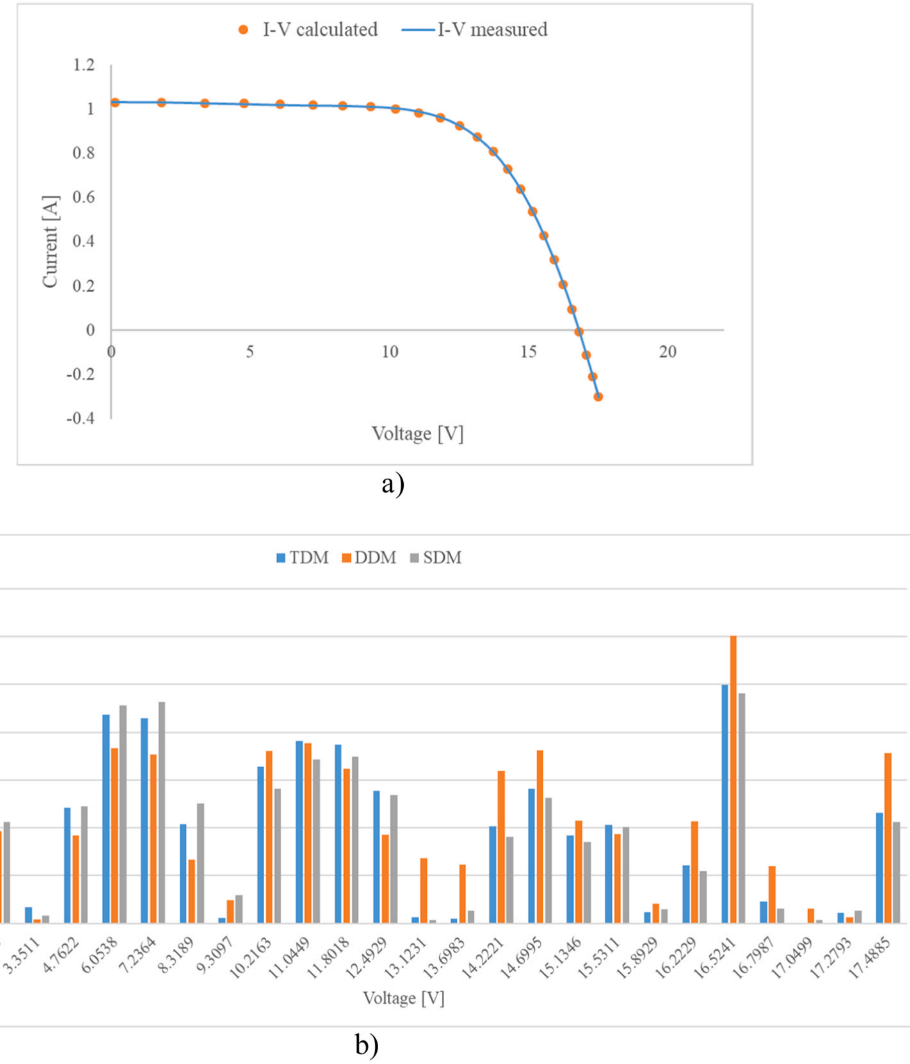


Fig. 4. PWP201 polycrystalline photovoltaic panel: a) Comparison between I-V characteristics measured and calculated using HSDA algorithm for TDM model; b) Absolute current errors for HSDA algorithm in the cases TDM, DDM, and SDM models.

$$I = I_{ph} - I_{o1}\left(e^{\frac{V+N_sIR_s}{n_1N_sV_T}} - 1\right) - I_{o2}\left(e^{\frac{V+N_sIR_s}{n_2N_sV_T}} - 1\right) - I_{o3}\left(e^{\frac{V+N_sIR_s}{n_3N_sV_T}} - 1\right) - \frac{V+N_sIR_s}{N_sR_{sh}} \tag{4}$$

3. Hybrid successive discretization algorithm

A metaheuristic algorithm called Successive discretization algorithm (SDA) was introduced in (Cotfas et al., 2019). The algorithm calculates the parameters of the PV cells and panels so that RMSE, see Eq. 5, is minimized.

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}(I_{kc} - I_{km})^2}{n}} \tag{5}$$

where n represents the number of (I,V) measurements, I_{kc} $(k = 1,2,\ldots,n)$ are the calculated values of the current of the PV cell or panel (using Eq. (3)), and I_{km} $(k = 1,2,\ldots,n)$ are the current measured values. Depending on the model used, each value I_{km} $(k = 1,2,\ldots,n)$ is calculated using Eqs. (1), (2) or (3). Since this paper is focused on the three diode model, it follows that:

$$I_{kc} = I_{\mathrm{ph}} - I_{o1}\left(e^{\frac{V_{km}+I_{km}R_s}{n_1V_T}} - 1\right) - I_{o2}\left(e^{\frac{V_{km}+I_{km}R_s}{n_2V_T}} - 1\right) - I_{o3}\left(e^{\frac{V_{km}+I_{km}R_s}{n_3V_T}} - 1\right) - \frac{V_{km}+I_{km}R_s}{R_{\mathrm{sh}}} \tag{6}$$

The idea behind SDA is discretization of continuous functions that helps to repeatedly improve the approximate solution. SDA is used for PV parameters extraction by computing a set of approximate solutions constructed by the discretization process (DP) so that the RMSE error is minimized (Cotfas et al., 2019). Then, a more refined DP is applied around each of these values and some approximate solutions are chosen. DP is repeatedly applied for a given number of iterations or until the solution is not improved anymore. The implementation details of DP for the TDM model are presented in what follows.

It is denoted by:

$$F_k^3(I_{\mathrm{ph}}, I_{o1}, n_1, I_{o2}, n_2, I_{o3}, n_3, R_s, R_{\mathrm{sh}}) = I_{kc} - I_{km} \tag{7}$$

Since the goal is to minimize RMSE for the photovoltaic cell or panel parameters, it follows that the objective function (denoted O) of the optimization problem can be considered as follows (ignoring the root

Table 4
Nine parameters extracted for STM6-40, RMSE and MAE.

Algorithm	I_{ph} [A]	I_{o1} [μA]	I_{o2} [μA]	I_{o3} [μA]	n_1	n_2	n_3	R_s [Ω]	R_{sh} [Ω]	RMSE [E-03]	MAE [E-03]	Rank
HSDA TDM	**1.66390717**	**4.89301E−4**	**7.43447E−7**	**3.4536759**	**36.0000487**	**35.9665112**	**59.634662**	**0.29403457**	**622.59273654**	**1.688808**	**1.10353**	**1**
HSDA DDM	1.6638773	1.10061101	1.68121367	-	53.3408920	65.8732649	-	0.16356557	580.97701828	1.720728	1.09234	-
HSDA SDM	1.66390477	1.73865439	-	-	54.730899	-	-	0.15385593	543.41834985	1.72981	1.09517	-
STF	1.66390774	4.8991E− 4	7.3737E−7	3.4513	36	36	59.634742	0.29440402	622.426402	1.688829	1.10621	2
EAGT	1.664	0.000	3.2445	4.6336E−4	72	59.184	36	0.286524	617.76	1.93224	1.34148	3
EMPO	1.664662	19.400	1.310	0.4630	975.02256	53.621784	59.466758	0.185976	529.64352	2.5421	1.43223	4
MPA	1.66412	1.24	5.56	2.20	53.46756	81.54	172.4004	0.13682	555.087	8.373065	3.02149	5

square and the division to n in Eq. 5):

$$O(I_{ph}, I_{o1}, n_1, I_{o2}, n_2, I_{o3}, n_3, R_s, R_{sh}) = \sum_{(I,V)} \left(F^3_{I,V}(I_{ph}, I_{o1}, n_1, I_{o2}, n_2, I_{o3}, n_3, R_s, R_{sh}) \right)^2 \tag{8}$$

Let $J_i = [a_i, b_i]$ (i=1,2,…,9) be the intervals of the definition domain, respectively for each of the nine parameters (P) I_{ph}, I_{o1}, n_1, I_{o2}, n_2, I_{o3}, n_3, R_s, and R_{sh} with the following constraints of the optimization problem: $P_i \in [a_i, b_i]$, where a_i is the minimum value of the P_i and b_i is its maximum value, respectively. We denote the domain of the problem by $D = J_1 \times J_2 \times J_3 \times J_4 \times J_5 \times J_6 \times J_7 \times J_8 \times J_9$ and call it the discretization 9D interval.

Since the objective function O is continuous on the domain D, the discretization process can be applied to O on D. The following text outlines the steps of discretization.

"A positive integer $d_i \in \mathbf{N}^*$ is considered (i = 1, 2, …, 9) for each interval J_i. Inside each of these 9 intervals the values v^i_j (j = 1, …, d_i) are taken so that" (Deaconu et al., 2020):

$$a_i < v^i_1 < v^i_2 < \ldots < v^i_{d_i} < b_i \tag{9}$$

For obtain a uniform distribution of the points in each interval J_i, the values v^i_j (j = 1, …, d_i) are calculated using Eq. 9:

$$v^i_j = a_i + j l_i \tag{10}$$

where:

$$l_i = \frac{b_i - a_i}{d_i + 1} \tag{11}$$

The parameters considered are:

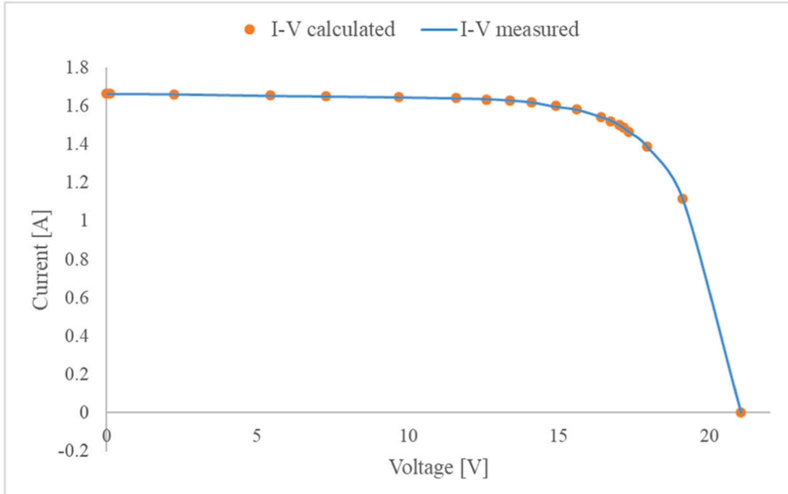
$$G = \left\{ \left(v^1_{j_1}, v^2_{j_2}, v^3_{j_3}, v^4_{j_4}, v^5_{j_5}, v^6_{j_6}, v^7_{j_7}, v^8_{j_8}, v^9_{j_9} \right) | j_i = 1, \ldots, d_i, i = 1, \ldots, 9 \right\} \tag{12}$$

Calculating the set G ends the discretization process. The best s values (having the lowest RMSE) are selected from G. Around each of these s values a DP is performed and the iteration of SDA ends. The best s values found in each iteration of SDA are used to start a new iteration. SDA stops after a given number of iterations or when no better solution is found. Finally, S denotes the best value computed in the last iteration of SDA. Consequently, the minimum root mean square found by SDA is:

$$\mathrm{RMSE}(S) = \sqrt{\frac{O(S)}{n}} \tag{13}$$

HSDA algorithm was introduced in (Cotfas et al., 2021) to calculate photovoltaic cell parameters. HSDA algorithm is hybridization between a known algorithm for photovoltaic cell parameters extraction and SDA. The former algorithm builds a solution that is named seed of SDA. Then, SDA is applied in a vicinity of the seed, and a better solution is calculated. For details of the calculation of this vicinity, see Eqs. (6–10) where i = 9 (Cotfas et al., 2021). If the newly found solution is inside the vicinity, then the algorithm stops. This last found solution is named *settled*. Otherwise, the calculated solution becomes a new seed and SDA performs a new iteration on its vicinity and so on. After each iteration of SDA, the newly calculated approximate solution has lower or equal RMSE than the previous one. Consequently, HSDA is also a tool for testing the optimality of a solution given by any algorithm for PV parameters extraction. If the solution is not optimum, then SDA computes a better one (Cotfas et al., 2021).

Previously, SDA and HSDA were successfully applied for the SDM and DDM models. The results were compared with other photovoltaic cell parameters obtained using different methods and algorithms. Since the results were very good (the best compared with the results from literature at the moment of publication), in this paper, is adapt HSDA (in parallel implementation (Deaconu et al., 2020)) to extract the parameters for the three diode model. Instead of optimization in a 6-dimensional space or 8-dimensional space, in the three diode model, the



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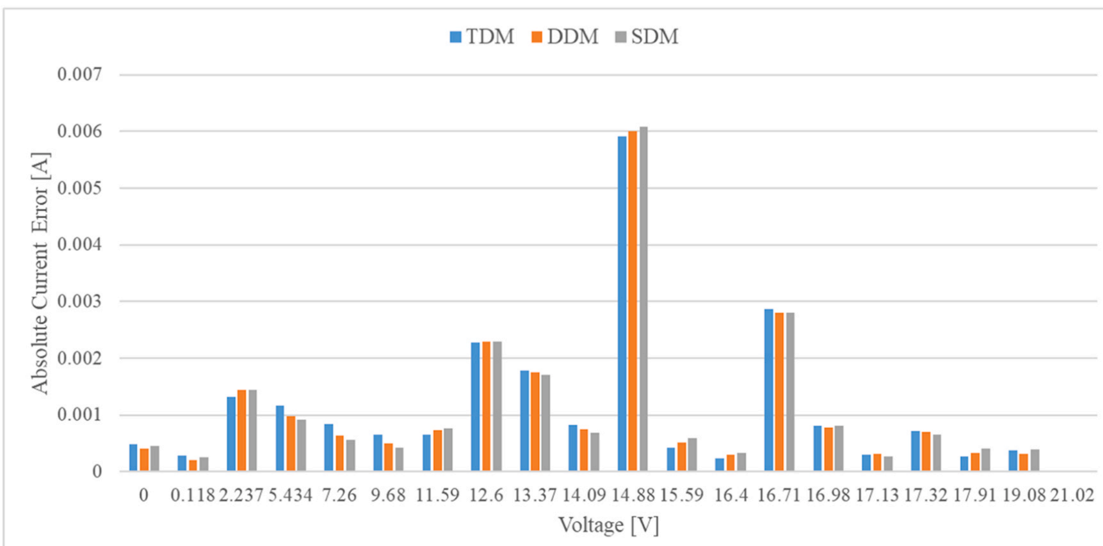


b)

Fig. 5. STM6–40 monocrystalline photovoltaic panel: a) Comparison between I-V characteristics measured and calculated using HSDA algorithm for TDM model; b) Absolute current errors for HSDA algorithm in the cases TDM, DDM, and SDM models.

optimization takes place in a 10-dimensional space. Consequently, the discretization applied to each of the 9 intervals is decreased in quality compared with the discretization applied on the intervals in the one or two diode model. Nevertheless, the results obtained with HSDA for the three diode model are very good, being better or (in some cases) much better than the results obtained from literature for existing datasets.

4. Results and discussion

Six datasets from the academic and research literature are considered to analyze the results obtained by HDSA algorithm in order to extract the nine parameters by using the TDM model. The considered datasets are for RTC France (Easwarakhanthan et al., 1986) and aSi (Cotfas et al., 2021), photovoltaic cells and PWP201 (Easwarakhanthan et al., 1986), STM6–40 (Jordehi, 2018), Kyocera KC200GT (Ma, 2014) and PVM 752 GaAs (Jordehi, 2018) photovoltaic panels

4.1. RTC France photovoltaic cell

The current-voltage dataset of RTC is one of the most frequently used and it is presented in Table S1. The measurement of the I-V characteristic is made at 1000 W/m^2 and 33 °C temperature.

Table 1 shows the extracted parameters of the RTC France photovoltaic cell using the SDM, DDM, and TDM models with the HSDA algorithm and the ones obtained with other algorithms using the TDM model. Additionally, RMSE, MAE and the ranking are considered. RMSE and MAE are calculated using the parameters from the papers.

The comparison has two steps. The first step is to compare the results obtained with the HSDA algorithm for all three models SDM, DDM, and TDM. The second step is to compare the results obtained with HSDA with the other ten algorithms for the TDM model.

Using the HSDA algorithm in the case of the triple diode model leads to a decrease of 1 % in RMSE in comparison with the other two models, SDM and DDM. This proves the superiority of the TDM model. There are high differences for two out of the nine parameters, as it can be seen in Table 1, R_{sh} and the second reverse saturation current.

For the second part of the analysis, the HSDA algorithm proves its superiority in comparison with other algorithms. The improvements in RMSE for HSDA algorithm varies from 0.4 % for OBEDO algorithm to 38.5 % for OBWOA. I_{ph} and R_s are the two parameters that vary slightly

Table 5
Nine parameters extracted for Kyocera KC200GT, RMSE and MAE.

Algorithm	I_{ph} [A]	I_{o1} [μA]	I_{o2} [μA]	I_{o3} [μA]	n_1	n_2	n_3	R_s [Ω]	R_{sh} [Ω]	RMSE [E-02]	MAE [E-03]	Rank
HSDA TDM	**8.19910680**	**3.99564E−5**	**3.0489E−5**	**3.790E−5**	**62.0581324**	**49.5674676**	**52.385462**	**0.28688325**	**110.05378220**	**1.1834046**	**8.94342**	**1**
HSDA DDM	8.1993730	3.7243E−4	3.9374E−5	-	62.8079934	49.4610340	-	0.28804863	110.034340	1.190362	9.09918	-
HSDA SDM	8.1861146	3.9544E−4	-	-	54.3328171	-	-	0.2654685	125.58895224	1.843933	14.2748	-
RGNDO	8.2011	0.001	0.001	0.001	56.5326	108	108	0.2484	99.456	3.738936	24.8205	2
WOA	8.1265	0.00102	3.47	0.00102	56.9484	100.1808	76.7448	0.2214	152.0232	4.680127	29.4512	3

while the reverse saturation currents, the ideality factor of diode, and the shunt resistance have a higher variation. These variations show that the algorithms don't find the global minimum. When comparing the parameters extracted using the HSDA and OBEDO algorithms, a significant difference is observed in the reverse saturation currents and ideality factors of the diode. These differences are due to the mechanisms of the photovoltaic cell. This highlights the complexity of the problem and the challenge of finding the global minimum without getting stuck in a local minimum. If two algorithms are taken into account, HSDA and MPA, with a difference in RMSE of only 1.7 %, a high difference of 28.1 % can be observed between shunt resistances, I_{01} by around 39 %, I_{02} by around 16.9 %, I_{03} very high, n_2 by around 57 % and n_3 is more than 100 %.

The HSDA algorithm accurately calculates the parameters for the TDM model, as evidenced by the very low root mean square error. Additionally, the I-V characteristic calculated using the HSDA algorithm closely matches the measured one for the TDM model, as shown in Fig. 2a.

The absolute error for each pair is shown in Fig. 2b in all three cases. For the TDM case the absolute error is lower for the majority of pairs than the ones for the SDM and DDM models. The absolute current error in the case of TDM model is 0.0211027, in case of DDM it is 0.0212354 and 0.0215278 in case of SDM respectively if the HSDA algorithm is used.

4.2. Amorphous silicon photovoltaic cell

The second photovoltaic cell considered is the amorphous silicon one with an area of 1 cm^2. The dataset is measured at 1000 W/m^2 irradiance and its temperature is 25 °C. It is presented in Table S2.

The estimated parameters of the aSi using the SDM, DDM, and TDM models with the HSDA algorithm is shown in Table 2. RMSE, MAE and the ranking are calculated. In specialized literature, no algorithms are applied on the amorphous photovoltaic cell dataset to extract their parameters in the case of TDM model. The comparison is made only with the other two models DDM and SDM.

The TDM model gives the best results for RMSE and MAE in the case of aSi photovoltaic cell. The RMSE is lower than the one for the DDM model with around 45 % and 53 % for the SDM model. A high difference can be observed for all parameters, least the photogenerated current.

The matching between the measured and calculated (I,V) pairs are presented in Fig. 3a and the comparison between the absolute current error for the three models are presented in Fig. 3b.

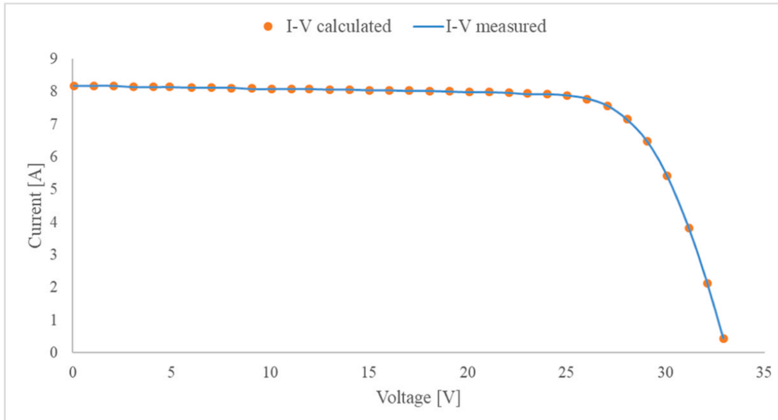
The absolute current error for most (I,V) pairs is substantially lower in the case of the TDM model in comparison with both models DDM and SDM. This confirms the superiority of the TDM models in comparison with the other two models.

4.3. PWP201 photovoltaic panel

The PWP201 polycrystalline photovoltaic panel has 36 cells connected in series. The I-V is measured at 1000 W/m^2 irradiance. The temperature of the cells was 45 °C. The dataset, the calculated current and the absolute current error for each (I,V) pair are presented in Table S3. The dataset for PWP201 polycrystalline photovoltaic panel is almost as commonly used as the dataset of the RTC France photovoltaic cell in the specialized literature.

The estimated parameters of the PWP201 polycrystalline photovoltaic panel using the SDM, DDM, and TDM models with the HSDA algorithm and the ones obtained with other algorithms using TDM model are shown in Table 3.

RMSE obtained with the HSDA algorithm in the case of the TDM model is the best one. The TDM model and the SDM model are practically equal, with very small differences between them. By comparing the DDM and TDM models it is concluded that the RMSE for TDM model is lower by 6.3 % than RMSE for the DDM model.The conclusion is that for



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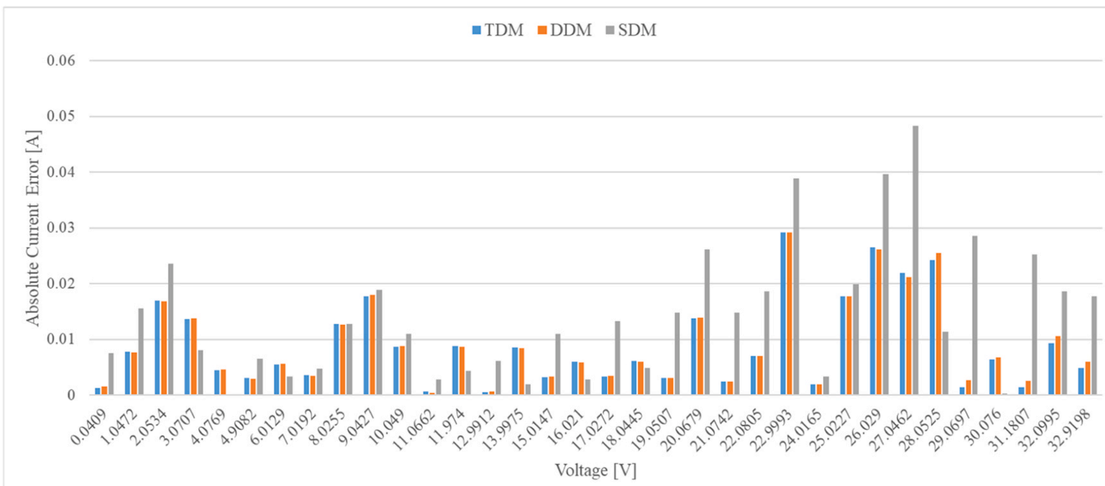


b)

Fig. 6. Kyocera KC200GT photovoltaic panel: a) Comparison between I-V characteristics measured and calculated using HSDA algorithm for TDM model; b) Absolute current errors for HSDA algorithm in the cases TDM, DDM, and SDM models.

the PWP 201 photovoltaic panel both models, SDM and TDM, can be applied. The SDM is simpler than the TDM model, and it is more conveniently used.

The superiority of the HSDA algorithm in the case of the TDM model in comparison with the other algorithms taken into account is proven through the lowest RMSE and MAE. The RMSE obtained with four algorithms are almost equal: HSDA, STF, OBEDO and MIGTO. In the case of MIGTO algorithm the TDM becomes DDM model because the reverse saturation current is zero. The decrease in RMSE varies from 1.2 % for GBO to 813 % for IGWO. In the case of COA with the parameters from Table 3 the matching with the I-V caracteristic is not good.

The matching between the I-V measured and the calculated one is very good and this can be seen from Fig. 4a. There is an alternation between the absolute current errors in the case of the pairs for the three models. It can be seen from Fig. 4b that the lowest value is not for the one model. The absolute current error is 0.05004801 for TDM,0.050479507 for SDM and 0.05487106 for DDM model. By analyzing these three values it can be concluded that the worst model for the PWP201 photovoltaic panel is DDM.

4.4. STM6-40 photovoltaic panel

The STM6–40 monocrystalline photovoltaic panel has 36 cells connected in series. The I-V characteristic is measured at 1000 W/m^2 irradiance. The temperature of the cells was 51 °C. The dataset, the calculated current and the absolute current error for each (I,V) pair are presented in Table S4.

The calculated parameters of the STM6–40 using the SDM, DDM, and TDM models with the HSDA algorithm and the ones obtained with the MPA algorithm using the TDM model is shown in Table 4.

The HSDA algorithm with TDM model has the best performance in both ways, in comparison with the other two models and with the MPA algorithm. The decreases in RMSE varies from 0.25 % for DDM model and 0.77 % for SDM model. RMSE for the TDM model is the lowest, but the difference in comparison with STF is very small. The values of the parameters for the two algorithms, HSDA and STF, are very similar, that show the algorithms found the global minimum. In comparison with the rest of the algorithms the difference varies from 12.4 % in the case of EAGT algorithm to 487 % in the case of MPA algorithm. The variation for parameters, in the case of comparison for algorithms, is high for I_{o2}, I_{o3}, n_3, and parasite resistance.

The matching between the I-V measured and calculated values is very good and this can be seen in Fig. 5a. There is an alternation between the absolute current errors in the case of the pairs for the three models. It can be seen from Fig. 5b that the lowest value is not for the one diode model. The absolute current error is 0.0222177 for TDM,0.0219033 for SDM and 0.0218468 for DDM model.

Table 6
Nine parameters extracted for PVM_752GaAs, RMSE and MAE.

Algorithm	I_{ph} [A]	I_{o1} [μA]	I_{o2} [μA]	I_{o3} [μA]	n_1	n_2	n_3	R_s [Ω]	R_{sh} [Ω]	RMSE [E-04]	MAE [E-05]	Rank
HSDA TDM	**0.09994877**	**1.08474E−9**	**6.11836E−3**	**0.7181430**	**1.21579999**	**2.55979654**	**5.4364000**	**0.72844606**	**1119.5367245**	**1.1326455**	**7.94479**	**1**
HSDA DDM	0.10005597	7.26941E−5	6.22556E−7	-	2.00260802	1.51479080	-	0.66900341	634.06199495	2.130617	16.9048	-
HSDA SDM	0.10002750	5.94434E−6	-	-	1.64669026	-	-	0.65014344	678.14612332	2.346967	18.1819	-
MIGTO	0.09990	0.00E+00	0.00E+00	1.86E−10	1.0000	1.0596	2.0000	0.7314	998.41	1.5093	9.9153	2
MPA	0.0999	1.08E−9	6.32E−03	0.199	1.2159	2.5576	4.9353	0.72603	1030.383	1.777177	11.777	3
OBEDO	0.09998	1.81E−6	6.65E−12	0.299	1.5696	1.2262	4.1442	0.6632	874.65	1.9516	14.234	4
TGA	0.1002	2.0068E−5	4.3812E−5	8.161E−5	1.9057	1.9057	1.9060	0.5439	700.3994	6.877588	46.5851	5
GWO	0.10059	6.82	0.205	32.5	15.194	2.958683	47.18298	0.147818	1486.179	-	-	6

4.5. Kyocera KC200GT photovoltaic panel

The Kyocera KC200GT multicrystalline photovoltaic panel has 54 cells connected in series. The I-V characteristic is measured at 1000 W/m^2 irradiance. The temperature of the cells was 25 °C. The dataset, the calculated current and the absolute current error for each (I,V) pair are presented in Table S5.

The calculated parameters of the Kyocera KC200GT panel using the SDM, DDM, and TDM models with the HSDA algorithm and the ones obtained with other two algorithms using TDM model are shown in Table 5.

The HSDA algorithm for the TDM model has the lowest RMSE. The RMSE for TDM model decreases by 0.6 % in comparison with DDM model and 55 % respectively for SDM model.

A comparison between HSDA and the two algorithms shows an improvement for both statistical tests. RMSE calculated with HSDA decreases 3.1 times in comparison with the one obtained with RGNDO and almost 4 times in comparison with the one obtained with WOA.

The matching between the I-V measured and the calculated one is very good and this can be seen in Fig. 6a. There is an alternation between the absolute current errors in the case of the pairs for the TDM and DDM models. The absolute current error for SDM model is higher than for the other two for almost all pairs. It can be seen from Fig. 6b that the lowest value is not for the one diode model. The absolute current error is 0.304076 for TDM, 0.485344 for SDM and 0.309372 for DDM model.

4.6. PVM_752GaAs photovoltaic panel

The dataset of the PVM_752GaAs thin film photovoltaic is obtained for 1000 W/m^2 irradiance. The temperature of the cells was 25 °C. The dataset, the calculated current and the absolute current error for each (I, V) pair are presented in Table S6.

The calculated parameters of the Kyocera KC200GT using the SDM, DDM, and TDM models with the HSDA algorithm and the ones obtained with other two algorithms using TDM model are shown in Table 6.

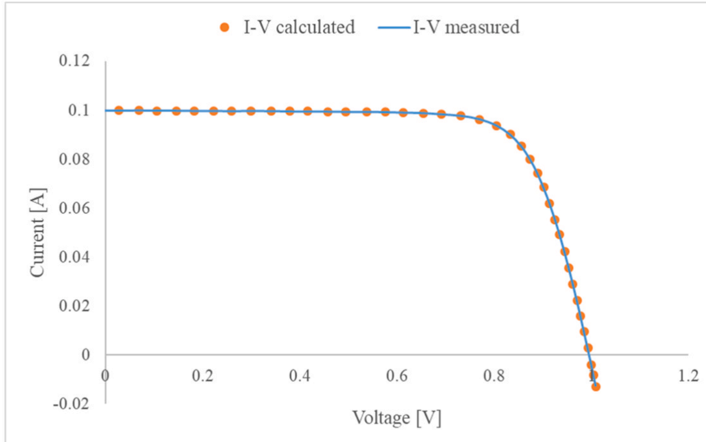
The HSDA algorithm for the TDM model has the lowest RMSE. The RMSE for TDM model decreases by 6 % in comparison with DDM model and 55 % respectively for SDM model.

A comparison between HSDA and the two algorithms shows an improvement for both statistical tests. The RMSE calculated with HSDA decreases by 25 % in comparison with MIGTO algorithm, 60 % in comparison with the MPA algorithm, around 6 times in comparison with the one obtained with TGA and for GWO algorithm the RMSE is too high for comparison. In the case of the MIGTO, the TDM model becomes practically the SDM model because two reverse saturation currents are zero.

The matching between the I-V values, measured and calculated, is very good and this can be seen in Fig. 7a. There is an alternation between the absolute current errors in the case of the pairs for all three models. It can be seen from Fig. 7b that the lowest value is not for the one diode model. The absolute current error is 0.00349571 for TDM, 0.00800002 for SDM and 0.00743812 for DDM model.

The number of iterations to obtain the minimum value of RMSE using HSDA algorithm is low, under 15 iterations. The computing time is relatively high, 46 s, in the case of a computer with features 8-thread i7 processor at 1.9 GHz. The time is reduced under 10 s, if a computer with Intel Core i9 processor at 3.6 GHz is used. The convergence characteristics of the RMSE for all six PV cells and panels is presented in Fig. 8.

The iterations number varies from 10 for Kyocera KC200GT panel to 14 for PVM_752GaAs panel. The highest number of iterations after the RMSE enter the region with the minimum is six for STM6–40 panel. This can be explained because the number of the (I,V) pairs is very low and not uniformly distributed.



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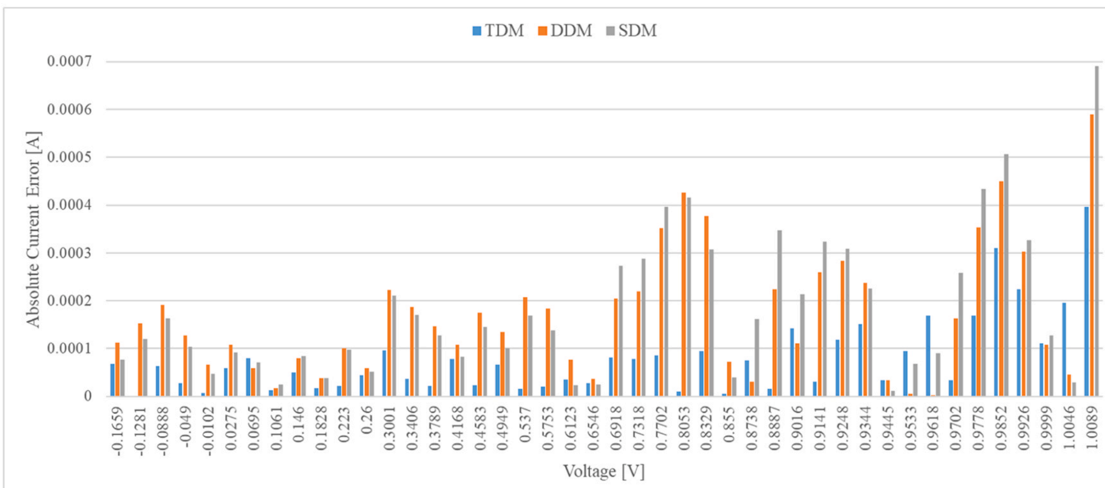

b)

Fig. 7. PVM_752GaAs photovoltaic panel: a) Comparison between I-V characteristics measured and calculated using HSDA algorithm for TDM model; b) Absolute current errors for HSDA algorithm in the cases TDM, DDM, and SDM models.

5. Conclusions

The HSDA algorithm is adapted and implemented for use in order to extract nine parameters given by the TDM model for two photovoltaic cells: amorphous silicon and RTC France, and four photovoltaic panels: PWP201, STM6–40, Kyocera KC200GT and PVM_752GaAs.

Two statistical tests RMSE and MAE are used to compare the performance of the HSDA algorithm with other algorithms published in the specialized literature. Additionally, the absolute current error is used to compare the results obtained by HSDA algorithm for all three models: TDM, DDM and SDM.

By analyzing the results obtained, the HSDA algorithm has the best results and it proves its supremacy in extracting the PV parameters in case of the TDM model. The RMSE calculated with it has the lowest value for the six devices under test. The improvement varies 0.4 % and 62.7 % for RTC, 0.003 % and almost three times for PWP201, 0.4 % and 62.7 % for RTC, 0.0012 % and almost five times for STM6–40, three and almost four times for Kyocera KC200GT, 32 % and six times for PVM_752GaAs.

The performance of the TDM model is better than the other two models, SDM and DDM**.** In the case of RMSE, the improvements of the TDM model in comparison with SDM and DDM models are: 0.9 % for both models of the RTC cell, 89 % for SDM and 84 % for DDM of the aSi, 0.002 % for SDM and 6.7 % for DDM of the PWP201, 2.4 % for SDM and 1.9 % for DDM of the STM6–40, 55.8 % for SDM and 0.6 % for DDM of the Kyocera KC200GT, 107 % for SDM and 88 % for DDM of the PVM_752GaAs. These results prove that the TDM model is necessary to be applied for a very good accuracy.

Although HSDA proves to be a very good tool for determining the parameters of PV cells and panels demonstrated by the results obtained, it should be mentioned that its accuracy is limited by the performance of the computer used and by the time available to calculate the parameters (since in order to get better results, more detailed DPs are necessary and so, the quantity of the calculations is considerably increased). As the other metaheuristics from literature, HSDA also cannot guaranty any accuracy or that it gives an approximate solution close to the global optimum. The number of iterations is very low, but the time for each of them is relative high, the computing time is around 10 s in a very good computer configuration.

In future work the HSDA algorithm adapted for TDM model will be used to calculate the parameters of the multijunction photovoltaic cell and for organic solar cells. Because HSDA has demonstrated its performance for six photovoltaic cells and panels, it will be used to extract parameters in various environmental conditions, especially irradiance and temperature. Another direction of further research is to use the parameters find out with the HSDA algorithm with TDM model to forecast the power generated by the photovoltaic panels.

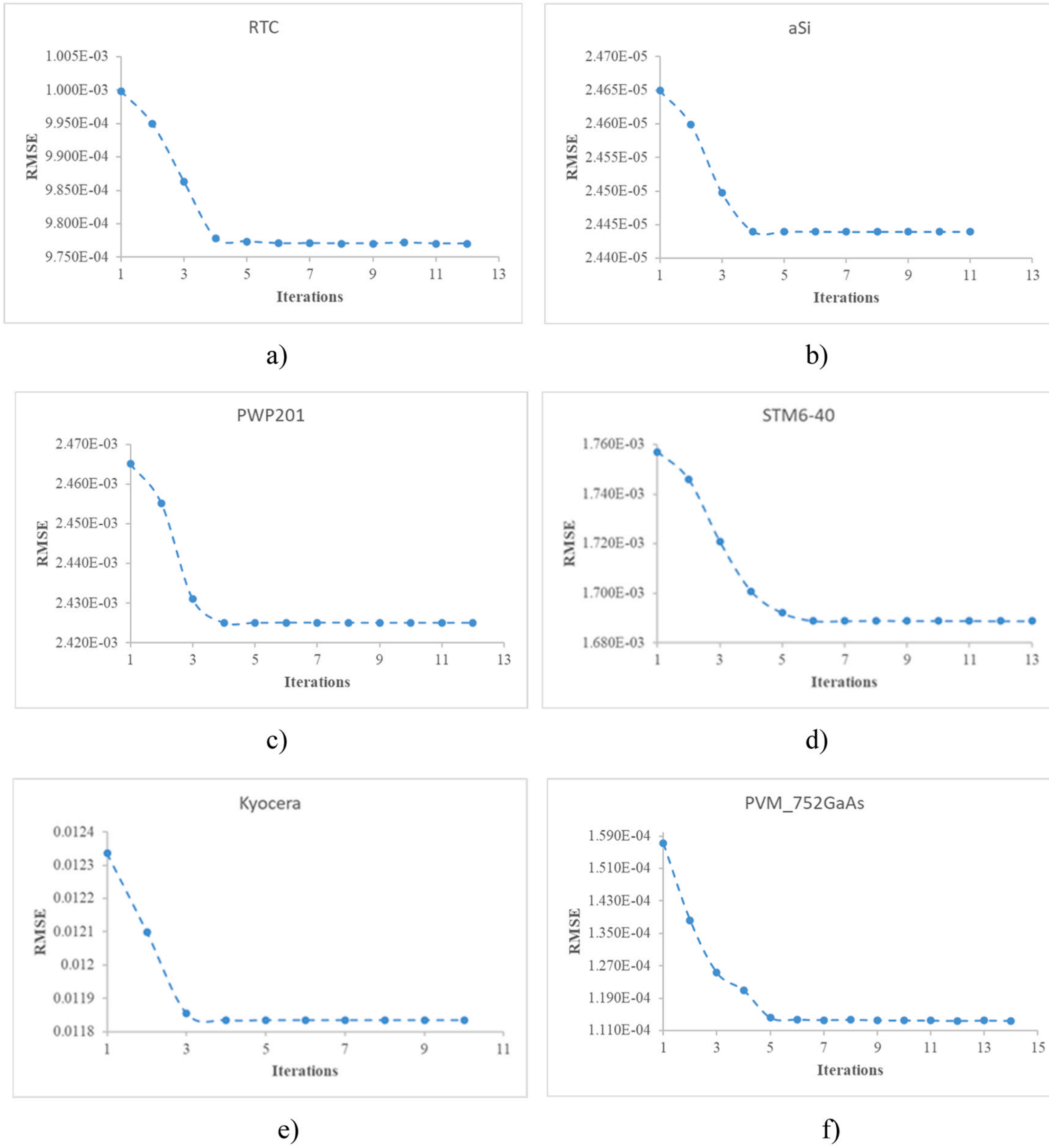

Fig. 8. Convergence characteristic for HSDA algorithm in the case of: a) RTC cell; b) aSi cell; c) PWP201 panel; d) STM6–40 panel; e) Kyocera KC200GT panel; f) PVM_752GaAs panel.

Declaration of Competing Interest

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.

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Author contributions statement

All the authors contributed equally to this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.egyr.2024.10.052.

Data Availability

Supplementary files

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