Highlights

Estimation of parameters for solar cells with S–shaped current–voltage characteristics using meta–heuristic algorithms

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- Proposed deep learning-based method to predict iron contamination in Si-SC by using IV curve.
- The simulated IV characteristics are used to create training and test datasets.
- The DNN's configurations are proposed.
- The mean squared relative error of prediction is up to 0.005.

Estimation of parameters for solar cells with S–shaped current–voltage characteristics using meta–heuristic algorithms

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ABSTRACT

Defect-assisted recombination processes frequently limit the photovoltaic device performance. The low-cost and express methods of impurity contamination control are in demand at solar cell manufacturing. In this paper, we applied deep learning-based approach to extract the iron concentration in silicon solar cell from an ideality factor values.

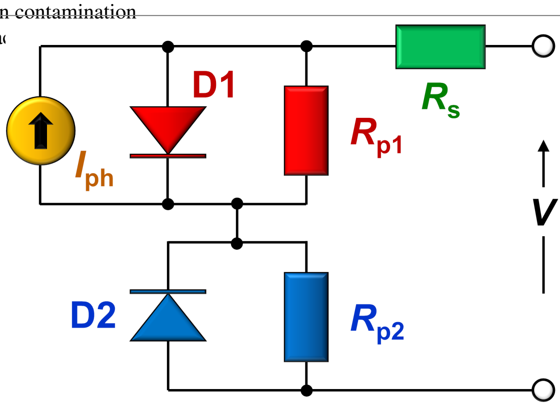

Figure 1: The opposed two–diode equivalent–circuit model of a solar cell.

1. Introduction

[1]

2. Problem definition

2.1. Solar cell model

Fig. 1 vividly reveals the structure of the used model [2]. It can be seen from the figure that model contains a current source accompanied by a diode D1, a shunt resistor R_{p1} to show the leakage current, and a series resistor R_s to consider the losses associated with the load current. Besides, the second diode D2 with a second parallel resistance R_{p2} is placed opposite to the first one and is essential to simulate the non-ideal effects of the active layer/cathode interface. In this model, D1 is responsible for the exponential behavior of the I–V curve, the main contribution of D2 is to simulate the S–shape. The analytical solution $V(I)$ of the opposed two–diode equivalent circuit model was obtained [3] using Lambert W-function [4]:

$$
\begin{aligned}
V \;=\; & (I+I_{ph}+I_{01})R_{p1} \\
& -\frac{n_1kT}{q}W\left\{\frac{qI_{01}R_{p1}}{n_1kT}\exp\left[\frac{qR_{p1}(I+I_{ph}+I_{01})}{n_1kT}\right]\right\} \\
& +\frac{n_2kT}{q}W\left\{\frac{qI_{02}R_{p2}}{n_2kT}\exp\left[-\frac{qR_{p2}(I-I_{02})}{n_2kT}\right]\right\} \\
& +(I-I_{02})R_{p2}+IR_s\,, \qquad (1)
\end{aligned}
$$

where I_{01} and I_{02} are the saturation currents and n_1 and n_2 are the ideality factors for D1 and D2 respectively, and I_{ph} is the ideal photocurrent. Thus, the model employs eight lumped parameters (I_{01}, n_1, R_{p1}, I_{02}, n_2, R_{p2}, R_s, and I_{ph}) that need to be determined from the I-V curve. Thus, from an optimization perspective, the dimension of the problem is $D = 8$.

The expression (1) has a drawback in that it tends to stray from the range of numbers that can be accommodated by the standard 64-bit floating-point format owing to the presence of exponential functions for larger numbers. To overcome this drawback, the use of the g–function $g(x) = \ln(W(\exp(x)))$ was suggested [5]. The analytical solution $V(I)$ using the g–function is as follows [5]

$$
\begin{aligned}
V(I) =& IR_s+\frac{n_1kT}{q}g(x_1)-\frac{n_2kT}{q}g(x_2) \\
& -\frac{n_1kT}{q}\ln\left[\frac{qI_{01}R_{p1}}{n_1kT}\right]+\frac{n_2kT}{q}\ln\left[\frac{qI_{02}R_{p2}}{n_2kT}\right], \qquad (2)
\end{aligned}
$$

with

$$x_1=\ln\left(\frac{qI_{01}R_{p1}}{n_1kT}\right)+\frac{q(I+I_{ph}+I_{01})R_{p1}}{n_1kT}, \qquad (3)$$

and

$$x_2=\ln\left(\frac{qI_{02}R_{p2}}{n_2kT}\right)-\frac{q(I-I_{02})R_{p2}}{n_2kT}. \qquad (4)$$

We used Eqs. (2)–(4) both for simulation IV curves and during the approximation procedure. The g–function was evaluated by using iterative procedure [5].

2.2. Synthetic IV curves

The research involved the parameter estimation of solar cells using meta-heuristic algorithms based on synthetic IV characteristics simulated using the opposed two–diode model. This approach allows for assessing the accuracy of the employed optimization methods, as the simulation was performed using known parameter values.

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In first part of the study, a detailed analysis was conducted on a single IV curve, evaluating the performance of meta–heuristic algorithms for parameter estimation in a one–time application mainly. Additionally, the suitability of employing two different fitness functions was examined. In the second part, we simulated a set of IV characteristics and evaluated the average performance metrics of various algorithms.

2.2.1. Single–IV case

Previous studies have demonstrated [6, 7] that when the ideality factor of D2 is either equal to or significantly larger than n_1 ($n_1 = n_2 = 1.92$ or $n_1 = 1.00$, $n_2 = 3.00$), the nonlinear least–squares method successfully determines a set of equivalent circuit parameters that accurately replicate the experimental data of an organic photovoltaic cell. Therefore this approach does not allow for distinguishing between similar IV curves obtained from solar cells with different parameters. To overcome this issue, Tada [7] successfully employed Bayesian estimation of parameters. To assess the capabilities of meta-heuristic methods in overcoming additional similar challenges, they were applied to a IV curve corresponding to such a problematic case. The parameter values were taken from [7]:

$$\begin{aligned} I_{01} &= 1.6 \cdot 10^{-6}\,\mathrm{mA}, \\ n_1 &= 1.92, \\ R_{\mathrm{p1}} &= 190\,\Omega, \\ I_{02} &= 0.16\,\mathrm{mA}, \\ n_2 &= 1.92, \\ R_{\mathrm{p2}} &= 190\,\Omega, \\ R_{\mathrm{s}} &= 45\,\Omega, \\ I_{\mathrm{ph}} &= 8\,\mathrm{mA}, \end{aligned} \tag{5}$$

and the IV curve was simulated over a range of 0-0.8 V with step 10 mV at $T = 300$ K. The simulation result is presented on Fig. 2 by symbols.

2.2.2. IV–set case

Employing various meta–heuristic algorithms to analyze a single IV curve is insufficient to obtain comprehensive insights into the methods' efficacy in parameter estimation. The accuracy of parameter determination is closely tied to their absolute values. For instance, an increase in the R_{p} value can pose challenges for accurately estimating resistance because the shunt will have a lesser impact on the overall shape of IV curve. In addition, the ratio between the parameter values also plays a crucial role.

To test the methods across different parameter values, we generated synthetic data in a temperature range from 260 K to 350 K. During the simulation process, we considered various temperature dependencies of the parameters. We based our approach on known physical mechanisms but focused on achieving the diversity of parameter ratio instead of attempting to replicate real–life photovoltaic converters precisely. Furthermore, an S–shaped IV curve is observed

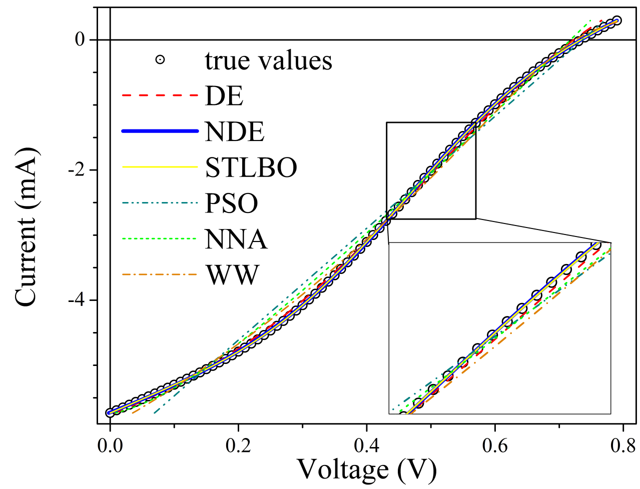

Figure 2: Fitting results (lines) for the simulated current-voltage characteristic (symbols). The values from Eq. (5) were assumed under simulation.

in solar cells of various types, and diverse charge transport mechanisms significantly complicate the selection of the only possible temperature dependence for each of the eight model parameters. Therefore, we assumed that the current conduction mechanism through D1 is close to tunneling, and hence, I_{01}, R_{p1}, and $(n_1 kT)$ remain constant, with $I_{01} = 0.015$ mA, $R_{\mathrm{p1}} = 10^4\ \Omega$, $n_1 kT = 7$ eV. In the case of D2, the thermionic emission current was suggested and I_{02} and n_2 increased and decreased, respectively, with temperature rise [8]:

$$I_{02} = I_{002} \exp\left(-\frac{E_I}{kT}\right), \tag{6}$$

$$n_2 = 1 + \frac{T^*}{T}, \tag{7}$$

where I_{002}, E_I, and T^* are the constants which are independent of temperature. The values of $I_{002} = 500$ A, $E_I = 0.40$ eV, and $T^* = 500$ K were used. For R_{p2}, an exponential temperature dependence was employed, as it is widely observed [9] in modern solar cells for the shunt resistance:

$$R_{\mathrm{p2}} = R_{\mathrm{p20}} \exp\left(\frac{E_R}{kT}\right). \tag{8}$$

with $R_{\mathrm{p20}} = 9$ mΩ, $E_R = 0.32$ eV. The linear temperature dependencies is expected for both I_{ph} [10, 11] and R_{s} [12, 13]:

$$y = y_0[1 + \mathrm{TC}_y(T - 300)], \tag{9}$$

where $y = I_{\mathrm{ph}}$ or R_{s}, y_0 is the parameter value at room temperature, TC_y is the temperature coefficient of parameter. For most types of monocrystalline silicon solar cells, the $\mathrm{TC}_{I_{\mathrm{ph}}}$ typically ranges from around $-0.0004\ \mathrm{K}^{-1}$ [14]. However, as the base thickness decreases, the temperature coefficient can increase to $-0.0014\ \mathrm{K}^{-1}$ [15]. For hydrogenated amorphous

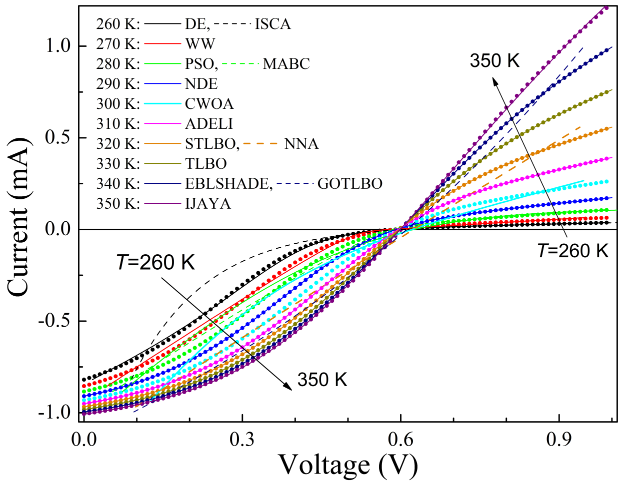

Figure 3: Fitting results (lines) for the simulated current-voltage characteristic (symbols). The values from Sec. 2.2.2 were assumed under simulation.

silicon solar cells, $\mathrm{TC}_{I_{\mathrm{ph}}}$ is equal to -10^{-3} K^{-1} [16]. For organic solar cells, the temperature coefficient can reach a magnitude of -0.003 K^{-1} [17]. During the simulation, we assumed $\mathrm{TC}_{I_{\mathrm{ph}}} = -10^{-3}$ K^{-1}. Furthermore, the values of $I_{\mathrm{ph0}} = 1$ mA, $\mathrm{TC}_{R_{\mathrm{s}}} = 0.02$ K^{-1}, and $R_{\mathrm{s0}} = 50\ \Omega$ were used.

The set of I–V data was composed of 10 curves, which were simulated at 10 K intervals from 260 to 350 K; in this case, n_1, I_{02}, n_2, R_{p2}, R_{s}, and I_{ph} varied from 6.37 to 4.73, from 9 to 880 μA, from 2.92 to 2.43, from $1.4\cdot10^4$ to 360 Ω, from 10 to 100 Ω, and from 0.96 to 1.05 mA, respectively. The simulation results are presented on Fig. 3 by symbols.

2.3. Meta-heuristic algorithms

In the literature, meta-heuristics are frequently categorized based on their sources of inspiration. This categorization involves incorporating elements of true simulations and principles that incorporate stochasticity, with the objective of emulating diverse characteristics observed in biological behavior, the lives of creatures in nature, human behavior, or natural phenomena. On this basis, any meta-heuristic algorithm can fall into one of the following main classes [18, 19, 20]: evolution-based methods (emulate the principles of evolutionary behavior observed in creatures in nature by relying on the concept of survival of the fittest), swarm intelligence–based methods (simulate the collective, dynamic, intelligent, and concerted gregarious conduct of collections of flocks or communities found in nature), bio–based methods (use biological processes unrelated to group behavior), chemical & physical–based methods (originate from the physical phenomena or chemical laws that exist in the universe), human-society–based methods (inspired by human beings, including various activities such as thinking and social behavior), and math–based methods (borrow the mathematical functions). Generally, there are hundreds of meta-heuristic optimization methods available. While we acknowledge that our selection may not be fully comprehensive, we utilized 14 methods, representing all classes mentioned above, to tackle the parameter estimation task within the framework of the opposed two-diode model for a solar cell. Hereafter, we provide a succinct description of each method alongside the parameters employed during the fitting process.

Differential evolution (**DE**). DE is one of the classical methods, and it is based on the natural selection law and uses the randomly generated initial population, differential mutation, and probability crossover [21]. During the implementation, we employed a penalty function suggested by Ishaque *et al* [22]. Besides, according to Wang and Ye [21], the values of mutation scaling factor $F = 0.8$, crossover rate $Cr = 0.3$, and population size $Np = 8 \times D = 64$ were used in this work.

Adaptive differential evolution with the Lagrange interpolation argument (**ADELI**). The method is based on DE, which integrates an adaptive local search scheme with Lagrange interpolation [23]. This incorporation aims to enhance the exploitation capability and accelerate the convergence speed. In ADELI, the scaling factor and crossover rate are set to self–adapting to optimize the results. We used parameter values recommended by Huang *et al* [23] during the implementation process. Additionally, we set Np to 64 for our numerical experiments.

Differential evolution with neighborhood–based adaptive evolution mechanism (**NDE**). The method uses a mutation strategy, which takes into account neighborhood and individual information, and an adaptive evolution mechanism [24]. The determination of F and Cr values is achieved through the utilization of the weighted adaptive procedure [25], and an adaptive adjustment of the population size is implemented using a simple reduction method (from $10 \times D = 80$ to 5).

Success history based DE with hybridization mutation strategies and population size reduction (**EBLSHADE**). The method is the hybridization framework between *pbest* and *ord_pbest* mutation strategies and stores a set of Cr and F values that have performed well in the recent past [26]. A linear Np reduction (from $18 \times D = 144$ to 4) is used as well.

Particle swarm optimization (**PSO**). It is another classic method based on observations of the social behavior of animals, such as bird flocking, fish schooling, and swarm theory. According to Ye et al. [27], the values of learning factors $l_1 = l_2 = 2$, the final weight and the initial weight $w_{max} = 0.9$, $w_{min} = 0.4$, and $Np = 15 \times D = 120$ are used in this work.

The *modified artificial bee colony* (**MABC**) algorithm is based on the intelligent foraging behavior of honey bee swarms [28]. The control parameters include the population size ($Np = 8 \times D = 64$) and the maximum number of generations after which each non-improved food source is to be discarded ($L_{imit} = 36$).

Chaotic Whale Optimization Algorithm (**CWOA**). WOA draws inspiration from the hunting behavior of humpback whales [29]. On the other hand, CWOA employs chaotic maps to compute and dynamically adjust its internal parameters [30]. In our study, we utilized the Singer chaotic map and set $Np = 100$ for the identification of the parameters of the solar cell.

The *Neural Network Algorithm* (**NNA**) is a meta-heuristic algorithm that draws inspiration from both biological nervous systems and artificial neural networks [31]. The recommended [31] value $Np = 50$ is used in our paper.

The *teaching learning based optimization* (**TLBO**) algorithm employs the concept of passing on knowledge within a classroom. Similar to learners acquiring knowledge from a teacher and interacting with their peers, TLBO incorporates such interactions [32]. In this study, a value of $Np = 100$ is utilized.

Generalized oppositional teaching learning based optimization (**GOTLBO**). This method integrates a concept that incorporates both the current estimate and its opposite estimate simultaneously into the original TLBO algorithm through the initialization step and generation jumping [33]. The values of jumping rate $Jr = 1.0$ and $Np = 20$ were used.

Simplified teaching-learning based optimization algorithm (**STLBO**). In STLBO, an elite strategy is employed to improve the searching capability, and a the chaotic map is used to enrich the uniformity of random values in the mutation phase [34]. The logistic chaotic map and $Np = 20$ were used.

Water wave optimization (**WWO**) takes inspiration from shallow water wave models and borrows ideas from wave propagation, refraction, and breaking [35]. WWO is easy to implement with a small-size population, and there are four control parameters: the maximum wave height h_{max}, the wavelength reduction coefficient α, the breaking coefficient β, and the maximum number k_{max} of breaking directions. According to Zheng [35], we used the values $h_{max} = 6$, $\alpha = 1.026$, $Np = 10$, $k_{max} = \min(12, D/2) = 4$, and β linearly decreased from 0.25 to 0.001.

Improved JAYA (**IJAYA**). Jaya algorithm is based on the concept that the solution obtained for a given problem should move toward the best solution and should avoid the worst solution and does not require any algorithm-specific parameter [36]. In IJAYA, a self-adaptive weight is introduced to adjust the tendency of approaching the best solution and avoiding the worst solution; an experience-based learning strategy is employed to maintain the population diversity and enhance the exploration ability, and a chaotic elite learning method is proposed to refine the quality of the best solution in each generation [37]. The logistic chaotic map and $Np = 4 \times D = 32$ were used.

Improved sine cosine algorithm (**ISCA**). SCA based on simulating the behaviors of sine and cosine mathematical functions [38]. ISCA implementation included a modified position-updating equation based on inertia weight ($w_{start} = 1$, $w_{end} = 1$), a nonlinear conversion parameter strategy based on the Gaussian function ($a_{start} = 2$, $a_{end} = 0$) [39], the creation of the opposite population to jump out from the local optima with $Jr = 0.1$ [40], a greedy selection, and $Np = 30$.

The majority of the utilized algorithms demonstrate excellent performance when it comes to parameter estimation of solar cells within conventional models (single or double diode) [30, 21, 33, 37, 28, 27, 34, 32, 41, 42].

In meta-heuristic optimization methods, the quality of the extracted parameters is evaluated using the fitness function at every iteration. In our investigation, absolute error and square error fitness functions were under consideration:

$$F_{\mathrm{AE}}(Y) = \sum_{k=1}^{p} \left| V^{\mathrm{tr}}(I_k) - V^{\mathrm{cal}}(I_k, Y) \right| , \tag{10}$$

$$F_{\mathrm{SE}}(Y) = \sum_{k=1}^{p} \left[V^{\mathrm{tr}}(I_k) - V^{\mathrm{cal}}(I_k, Y) \right]^2 , \tag{11}$$

where $V^{\mathrm{tr}}(I_k)$ is the simulated value of voltage at current I_k, $V^{\mathrm{cal}}(I_k, Y)$ is the calculated values of voltage, which can be obtained by Eqs. (2)–(4), for given set of parameters (i.e. $Y = \{I_{01}, n_1, R_{\mathrm{p1}}, I_{02}, n_2, R_{\mathrm{p2}}, R_{\mathrm{s}}, I_{\mathrm{ph}}\}$) at current I_k, and p is the total number of voltage steps in the IV characteristic.

We executed each tested algorithm for $N_{\mathrm{runs}} = 51$ independent runs on each simulated IV curve to generate the statistical results. The search ranges were set as follows: $I_{01}(\mathrm{mA}) \in [10^{-13}, 1]$, $n_1 \in [0.5, 50]$, $R_{\mathrm{p1}}(\Omega) \in [10, 10^6]$, $I_{02}(\mathrm{mA}) \in [10^{-7}, 10]$, $n_2 \in [0.5, 50]$, $R_{\mathrm{p2}}(\Omega) \in [10, 5 \cdot 10^4]$, $R_{\mathrm{s}}(\Omega) \in [0.1, 1000]$, $I_{\mathrm{ph}}(\mathrm{mA}) \in [10^{-3}, 100]$.

2.4. Evaluation metrics

To better show the performance differences between compared algorithms, several evaluation metrics are considered, which can be described as follows:

1. Mean value (MEAN), median value (MEDIAN), standard deviance (STD), and interquartile range (IQR) for each two–diode model parameter y (y is one of $\{I_{01}, n_1, R_{\mathrm{p1}}, I_{02}, n_2, R_{\mathrm{p2}}, R_{\mathrm{s}}, I_{\mathrm{ph}}\}$). MEAN and MEDIAN are often used to measure the solution quality. The closer the obtained MEAN and MEDIAN values are to the actual parameter values, the closer the obtained solution is to the optimal solution. To quantify, we used the absolute percentage of error (APE):

$$\mathrm{APE}\,(y) = \left| \frac{y - y^{\mathrm{tr}}}{y^{\mathrm{tr}}} \right| , \tag{12}$$

   where y^{tr} is the parameter value used during the IV curve simulation. APE was calculated for y_i, obtained by one–run algorithm application (APE_i), MEAN ($\mathrm{APE}_{\mathrm{MEAN}}$), and MEDIAN ($\mathrm{APE}_{\mathrm{MEDIAN}}$). Reducing STD and IQR result in a more stable algorithm performance.
2. Another evaluation criterion used to compare the algorithms' performance is to compare their execution time. We used average run time t_{run} in seconds for an individual optimizer on one IV curve.

3. Root mean square percentage of error (RMSPE) is a statistical measure that indicates how well the fitted curve matches the actual IV curve:

$$\mathrm{RMSPE} = \sqrt{\frac{1}{p}\sum_{k=1}^{p}\left[\frac{V^{\mathrm{tr}}(I_k) - V^{\mathrm{cal}}(I_k, Y)}{V^{\mathrm{tr}}(I_k)}\right]^2}. \quad (13)$$

4. Wilcoxon signed-rank test is a nonparametric statistical test used for pairwise comparisons of algorithms. This test assigns a rank to all the scores considered as one group and then sums the ranks of each group.
5. Friedman, Friedman Aligned Ranks, and Quade tests are used for comparing the performance differences among optimization algorithms (multiple comparisons $1 \times N$ with a control method). Therefore, the average rankings of the algorithms according to the tests are reported. Besides, the post–hoc Finner, Holm, Hochberg, and Holland procedures are used to establish proper comparisons between each algorithm and a set of other algorithms.
6. Multiple Comparison Test (Friedman) with Shaffer's static, Nemenyi, and Holm procedures are employed to compute all possible pairwise comparisons between groups ($N \times N$) and identify the differences.

3. Numerical results and discussion

3.1. Comparison of algorithms time

In meta–heuristic algorithms, a different termination can be defined. For instance, a termination condition can be a specific number of iterations N_{it}, constraints on the number of fitness function evaluations N_{FE}, a specific rate of precision, a specific time, no sign of change in solutions after a specific number of iterations, or a combination of these cases [43]. In this study, the primary focus was on the accuracy of parameter estimation. Therefore to ensure that both exploration and exploitation processes could be fully realized by each algorithm with an equal opportunity, the termination criterion used was the absence of changes in the solution. Based on this condition, the required number of iterations N_{it} was determined, and the corresponding calculation time was measured t_{run}. In addition, the N_{FE} was evaluated.

All the applied algorithms have been coded and implemented in Embarcadero®Delphi 10.3 programming software. The run time was estimated by using WinAPI-functions *QueryPerformanceCounter()* and *QueryPerformanceFrequency()*. The experiments were performed on Windows 10 Pro 64-bit, 2.9 GHz AMD Ryzen 7 4800H CPU, and 8 GB RAM.

The obtained results are listed in Table 1. As can be seen from the table, the number of iterations required for an algorithm does not always correlate directly with the number of fitness function evaluations or computation time needed to converge. The reason is the unique features of each algorithm. The run time of the algorithms varies considerably, with a range of 1.5 seconds to 93 seconds. Notably, WW, ISCA, NNA, and STLBO converge the fastest, while ADELI, TLBO, and MABC require the most time.

Table 1
Comparison of optimization algorithms for single IV curve parameter estimation

Algorithm	N_{it}	N_{FE}	t_{run} (s)
DE	8000	1024000	42 ± 1
EBLSHADE	3000	444600	22 ± 1
ADELI	12000	1800000	93 ± 2
NDE	5000	430000	20.2 ± 0.3
MABC	8000	1024000	48 ± 11
TLBO	5000	1000000	56.1 ± 0.3
GOTLBO	6000	360000	15 ± 1
STLBO	13000	273000	13.8 ± 0.3
PSO	4000	480000	19 ± 3
IJAYA	30000	960000	37 ± 1
ISCA	5000	150000	6.5 ± 0.1
NNA	5000	250000	10.6 ± 0.5
CWOA	3000	300000	16.6 ± 0.5
WW	3000	35000	1.4 ± 0.1

Table 2
Wilcoxon signed ranks test results of fitness functions comparison with a level of significance $\alpha = 0.05$

Algorithm	Parameter								
	I_{01}	n_1	R_{p1}	I_{02}	n_2	R_{p2}	R_{s}	I_{ph}	RMSPE
DE	SE	SE	=	=	SE	SE	=	=	=
EBLSHADE	SE	=	=	=	=	=	=	=	AE
ADELI	SE	=	=	=	=	=	=	=	AE
NDE	=	=	=	=	=	=	=	SE	SE
MABC	=	SE	=	=	=	=	=	=	SE
TLBO	SE	SE	SE	SE	SE	SE	SE	SE	SE
GOTLBO	=	=	=	=	=	SE	=	=	=
STLBO	SE	=	=	=	=	=	=	=	AE
PSO	=	=	=	=	=	=	AE	=	=
IJAYA	AE	AE	=	=	SE	=	=	=	=
ISCA	=	=	=	=	=	=	=	=	=
NNA	=	=	=	=	=	=	=	=	SE
CWOA	=	=	SE	=	AE	=	=	=	SE
WW	=	=	SE	=	AE	=	=	=	SE

3.2. Fitness function selection

To choose the more suitable fitness function, we evaluated each algorithm using the IV curve generated from the parameters provided in Eq. (5) with both F_{AE} and F_{SE} functions (see Eqs. (10) and (11)). Afterward, the results obtained using each of the functions were compared through pairwise comparisons. Table 2 gives the statistical results produced by Wilcoxon sign-rank test with a significant level $\alpha = 0.05$. A cell marked with the symbol "SE" indicates that evaluation of parameter specified in the column by the algorithm with F_{SE} outperforms result obtained by this algorithm with F_{AE}. A cell marked with the symbol "AE" indicates better results for function F_{AE}. In the case of the symbol "=", there is no significant difference between function F_{SE} and function F_{AE} aplication.

As evidenced in the provided data, utilizing the square error fitness function more frequently yields better outcomes

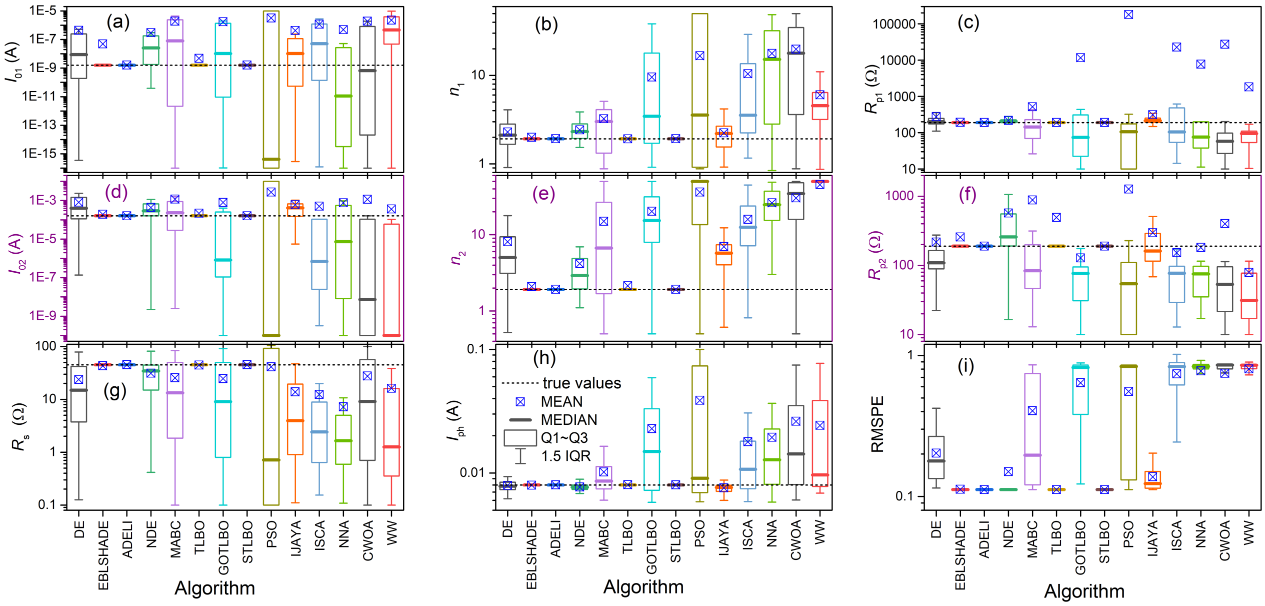

Figure 4: Box–plot of two–diode model parameter evaluation from single IV curve using different optimizers. The squares are the mean values, and the dashed lines correspond to the true parameter values.

in comparison to F_{AE}. In rare cases, the absolute error fitness function can enhance the alignment between the fitted and actual curves, as well as improve the accuracy of some parameter evaluations by PSO, IJAVA, CWOA, and WW algorithms. However, RMSPE is not the most crucial factor in determining model parameters, and the mentioned methods, as will be shown later, do not provide the highest accuracy. As such, the results presented in the following sections are exclusive to the application of the F_{SE} function. Therefore, it can be recommended that researchers consider the square error fitness function as a more effective and reliable option for the task of opposed two–diode model parameter evaluation.

3.3. Performance comparison

3.3.1. Evaluation of single–IV

In this subsection, we show and analyze the statistical results of different meta-heuristic algorithm applications to an IV curve, simulated with Eq. (5) values. Several typical fitting results of the synthesized curve are shown in Fig. 2. A more comprehensive version, including the fitting results obtained using each algorithm, is provided in the supplementary materials (figure S1). It can be seen, that the closest match between the approximation curves and the IV curve points is observed for EBLSHADE, ADELI, NDE, IJAYA, TLBO, and STLBO. On the contrary, the PSO and GOTLBO fitting curves had the least replication of the original data.

Fig. 4 shows the results of cell parameters evaluation by comparative algorithms. In addition, the figure presents the RMSPE data, which confirms the conclusions of the visual comparison between the fitting lines and the points of the IV curve. The results in terms of MEAN, MEDIAN, STD, and IQR are tabulated as well (table S1 in the supplementary material).

We would like to stress the following. In most cases, median values are more relevant to the actual parameter values than the mean values. Possible exceptions only apply to the evaluation of R_s and R_{p2} only. However, in cases where a method allows for parameter estimation with high accuracy (EBLSHADE, ADELI, TLBO, and STLBO), MEDIANs are at least as good as the MEANs. As a result, we will utilize median values as a robust measure of central tendency in nonparametric statistical tests. Secondly, the increase in algorithm stability (reduction in STD and IQR values) in determining each model parameter correlates with the accuracy of parameter evaluation. Furthermore, IQR values are generally no worse than STD values. Finally, small RMSPE values (close match between the fitting curve and the IV points) do not always indicate high accuracy in determining the parameters of a solar cell — see IJAYA and NDE data. For example, the difference between the $\mathrm{MEDIAN}_{\mathrm{RMSPE}}$ values for NDE and ADELI is approximately 0.0001 (about 0.08% of their absolute value). At the same time, in the ADELI case, the values of $\mathrm{APE}_{\mathrm{MEDIAN}}$ do not exceed $6 \cdot 10^{-4}$ for all model parameters evaluation, whereas for the NDE algorithm application, the obtained $\mathrm{APE}_{\mathrm{MEDIAN}}$ values are significantly higher and range from 0.04 for I_{ph} to 11.4 for I_{01}. On one hand, this confirms the issue identified by Tada [6, 7], which arises when estimating parameters according to the opposed two–diode model from similar IV curves corresponding to photovoltaic cells with distinct characteristics. Furthermore, the results indicate that some metaheuristic algorithms, such as NDE and IJAYA, can fall into a similar trap. On the other hand, the high accuracy in parameter estimation demonstrated by EBLSHADE, ADELI, and STLBO indicates that these algorithms are able to overcome the mentioned issue when applied. It should be noted that a similar problem has been previously addressed by employing Bayesian estimation of parameters [7]. However, each Bayesian calculation took approximately half a day on a computer better equipped than ours [7]. In our case, when applying meta–heuristic algorithms, the worst–case run time did not exceed 100 seconds.

In order to statistically compare the algorithm under consideration, we use nonparametric tests. In the single–IV case, all nonparametric statistical tests were used to compare the performance of meta–heuristic algorithms in assessing each of the eight model parameters. The APE_i values were used, and the number of case problems in the study n was equal to $N_{\mathrm{runs}} = 51$. Additionally, algorithms were compared in terms of curve-fitting accuracy by using RMSPE values. Furthermore, tests were employed for a composite parameter as well. This parameter, referred to as "Comp" hereafter, includes $\mathrm{APE}_{\mathrm{MEDIAN}}$ for each of the eight defined model parameters, the median value for RMSPE, and t_{run}. This parameter may provide the most valuable insights for comparing algorithms. However, it is important to note that the value of n is only 10. According to Derrac *et al* [44], the number of case problems should be $n \geq 2k$, where k is the number of algorithms ($k = 14$ in our study). Therefore, the use of the Comp parameter is not strictly rigorous. Indeed, it would have been possible to increase the n value using, for example, $\mathrm{APE}_{\mathrm{MEAN}}$. However, considering the deliberate utilization of a suboptimal parameter would have appeared inappropriate.

Fig. 5 graphically show the non–parametric statistical results of pairwise comparisons of algorithms based on the Wilcoxon signed–rank test. In the case of Comp comparisons, the differences in performance scores were normalized to the interval [0, 1]. As seen from the figure, no algorithm outperforms all others in evaluating each parameter. Furthermore, no algorithm surpasses all others in the evaluation even a single parameter. For example, as the figure states, STLBO shows a significant improvement over DE, NDE, MABC, GOTLBO, PSO, IJAYA, ISCA, NNA, CWOA, and WW across all the parameters considered with a level of significance $\alpha = 0.05$. Simultaneously, it was not detected the significant differences between STLBO and both EBLSHADE and ADELI for all parameter evaluations as well as between STLBO and TLBO in the Comp case. EBLSHADE outperforms nearly all other algorithms in the composite parameter, except for STLBO. According to the Wilcoxon test victories number, the worst performances are exhibited by PSO and CWOA. PSO achieved better results than ISCA, NNA, and CWOA in terms of RMSPE value, as well as outperformed WW in n_2 evaluation and RMSPE. Test detected significant differences between CWOA and WW in n_2 and I_{01} evaluations, between CWOA and PSO in I_{01}, I_{02}, R_{s}, and I_{ph} evaluations), and between CWOA and both ISCA and NNA in R_{s} evaluation case only.

Looking at the results of the Wilcoxon signed-rank test from another perspective, it can be observed that neither EBLSHADE nor STLBO had any defeats in pairwise comparisons, while ADELI had only one loss. ADELI was only outperformed by EBLSHADE in terms of the Comp parameter, primarily due to its significantly longer run time. The highest number of defeats was observed for the PSO and WW algorithms (104 and 84, respectively). The data regarding the total number of wins and losses when applying the Wilcoxon test for each algorithm are summarized in Fig. 6.

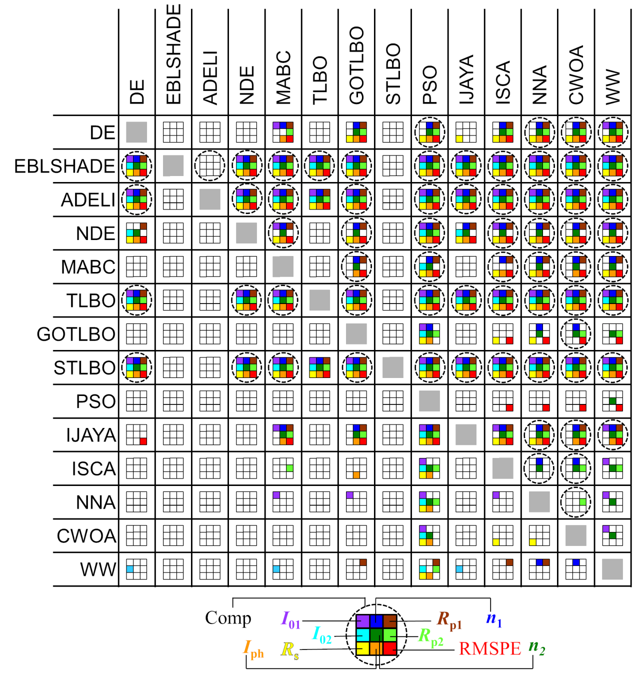

Figure 5: The results of Wilcoxon signed-rank test with a level of significance $\alpha = 0.05$ in the single-IV case. Each colored small square indicates that the algorithm specified in the row outperforms the algorithm specified in the column in evaluating one of the parameters of the two–diode model. The correspondence between the color and position of the square to a model parameter is shown in a legend at the figure bottom. The advantage of the row algorithm in the Comp parameter is indicated by the presence of a dashed circle.

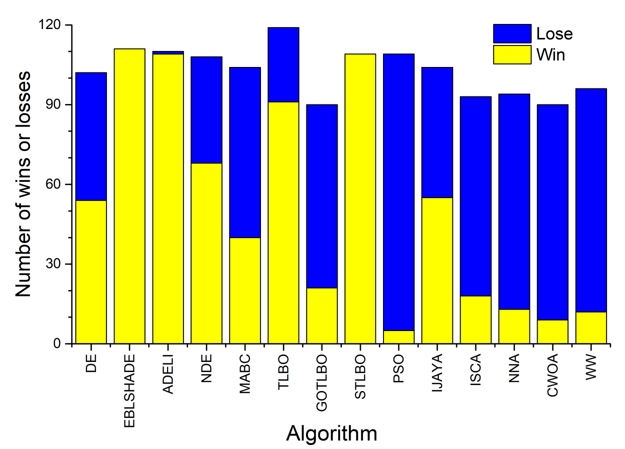

Figure 6: The total number of wins and losses for each algorithm in pairwise comparisons using the Wilcoxon signed-rank test with a significance level of $\alpha = 0.05$ in the single-IV case.

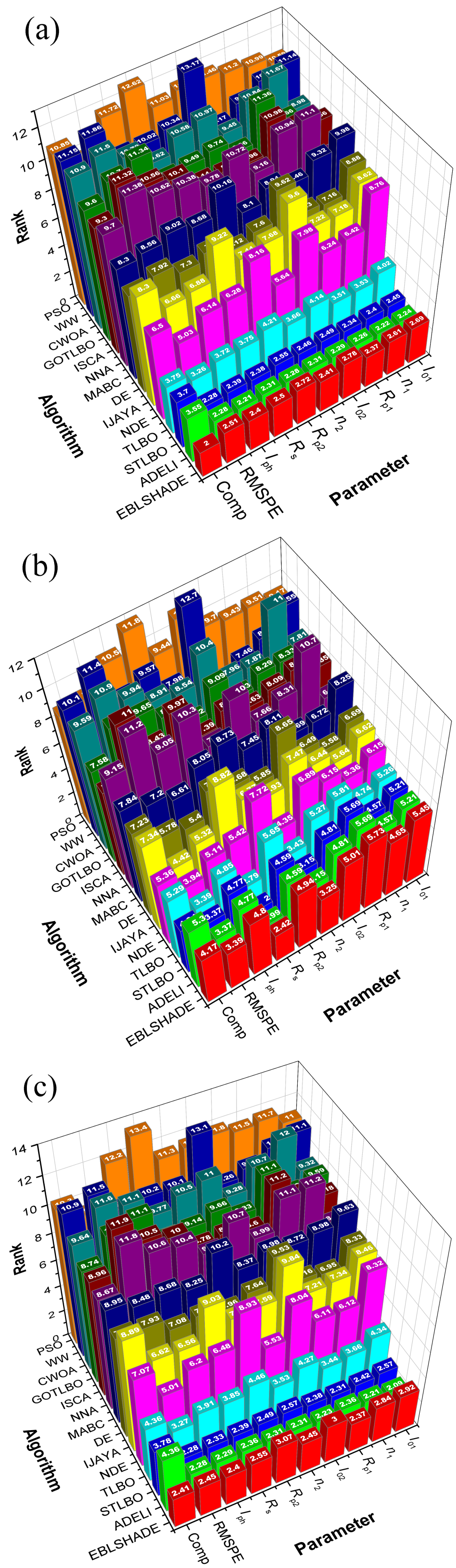

Figure 7: Ranking of the algorithms according to Friedman (a), Friedman Aligned (b), and Quade (c) tests in the single-IV case.

It is recommended [44] to begin the multiple comparison tests by examining the null hypothesis H_0, which asserts the equality of medians between the populations of results obtained by different algorithms. The null hypothesis p–values computed through the statistics of Friedman, Friedman Aligned, and Quade test and the Iman–Davenport extension are given in the supplementary material (table S2). The highest observed $p(H_0)$–values were found to be $2.7 \cdot 10^{-5}$ (Friedman Aligned test for the task of R_{p1} evaluation), $4.4 \cdot 10^{-4}$ (Friedman Aligned test for the composite parameter case), and $8.3 \cdot 10^{-6}$ (Quade test, Comp parameter). Thus obtained data strongly suggest the existence of significant differences among the considered algorithms in the accuracy of all model parameter determination, RMSPE values, and Comp parameter.

Fig. 7 shows ranks achieved by the Friedman, Friedman Aligned, and Quade tests for applied optimization algorithms in different tasks. Ranks are tabulated in the supplementary material as well (table S3). In almost all cases, the algorithms EBLSHADE, ADELI, and STLBO consistently achieve the top (smallest value) three ranks. For example, in assessing the accuracy of model parameter evaluation, ADELI has ranked first 22 times. The STLBO algorithm ranked first six times, taking the sole first place twice (I_{01} evaluation according Friedman Aligned test and R_{p1} evaluation according Quade test) and sharing it with ADELI four times (n_1, R_{p1}, n_2, and I_{ph} evaluation according Friedman Aligned test). In the RMSPE value case, ADELI and STLBO achieved equal and best ranks by all three used tests. When comparing based on the Comp parameter, the STLBO algorithm obtained the top rank according to the Friedman Aligned test, while the Friedman and Quade tests recognized EBLSHADE as the best. In most cases, the TLBO algorithm secured the fourth position, and in four cases, it even ranked third. In the majority of cases, the TLBO algorithm consistently ranked fourth out of all the algorithms tested. Interestingly, in four cases (I_{01} evaluation, RMSPE value, and Comp parameter by Friedman Aligned test, and Comp parameter by Quade test), it even achieved a commendable third-place ranking. We must note that overall, the absolute values of ranks for ADELI, STLBO, EBLSHADE and TLBO algorithms differ little, and the difference between the first and fourth ranks is often less than 0.5. The worst ranks are observed for PSO, NNA, CWOA, and WW.

It is known [44] that the Friedman, Friedman Aligned, and Quade tests are insufficient in establishing accurate comparisons between the algorithms considered. To compare a control method (1 of 14 compared) with a set of other algorithms (rest 13), one can define a family of hypotheses related to the control method. Applying a post-hoc test makes it possible to obtain a p–value that indicates the extent to which each hypothesis can be rejected. We calculated p–values using four post-hoc procedures (Finner, Holm, Hochberg, and Holland) for all algorithms, tests, and tasks. By following the indications given for the four post-hoc procedures considered, Table 3 shows the p–values obtained, using the ranks computed by the Friedman, Friedman

Table 3
Adjusted p-values for Friedman, Friedman Aligned, and Quade tests in single–IV case. ADELI is the control algorithm, and the task of R_{p1} evaluation is under consideration.

Algorithm	Test	post-hoc procedure			
		Finner	Holm	Hochberg	Holland
GOTLBO	Friedman	<1E-13	<1E-13	<1E-13	<1E-13
	Friedman Aligned	2.23361E-09	6.87266E-09	6.87266E-09	6.87266E-09
	Quade	2.57827E-03	4.09880E-03	3.90245E-03	4.09117E-03
PSO	Friedman	<1E-13	<1E-13	<1E-13	<1E-13
	Friedman Aligned	<1E-13	<1E-13	<1E-13	<1E-13
	Quade	2.57827E-03	2.58134E-03	2.58134E-03	2.57827E-03
MABC	Friedman	6.35048E-13	1.61204E-12	1.61204E-12	1.61204E-12
	Friedman Aligned	7.88131E-06	2.97065E-05	2.97065E-05	2.97062E-05
	Quade	1.73550E-02	6.56791E-02	6.56791E-02	6.38590E-02
WW	Friedman	1.84926E-10	5.69003E-10	5.69003E-10	5.69003E-10
	Friedman Aligned	3.15599E-13	8.01137E-13	8.01137E-13	8.01137E-13
	Quade	5.31725E-03	1.96611E-02	1.96611E-02	1.94928E-02
DE	Friedman	4.61292E-09	1.59678E-08	1.59678E-08	1.59678E-08
	Friedman Aligned	3.62181E-04	1.33738E-03	1.33738E-03	1.33663E-03
	Quade	7.62673E-02	2.85885E-01	2.49968E-01	2.53918E-01
IJAYA	Friedman	6.88175E-09	2.54096E-08	2.54096E-08	2.54096E-08
	Friedman Aligned	8.79672E-04	3.04543E-03	3.04543E-03	3.04172E-03
	Quade	7.62673E-02	2.85885E-01	2.49968E-01	2.53918E-01
CWOA	Friedman	8.73483E-09	3.29236E-08	3.29236E-08	3.29236E-08
	Friedman Aligned	4.27917E-09	1.58000E-08	1.58000E-08	1.58000E-08
	Quade	2.57827E-03	5.93402E-03	5.93402E-03	5.91840E-03
NNA	Friedman	1.17491E-08	4.33811E-08	4.27586E-08	4.33811E-08
	Friedman Aligned	2.23361E-09	7.25937E-09	7.25937E-09	7.25937E-09
	Quade	2.57827E-03	4.09880E-03	3.90245E-03	4.09117E-03
ISCA	Friedman	1.23525E-08	4.33811E-08	4.27586E-08	4.33811E-08
	Friedman Aligned	<1E-13	<1E-13	<1E-13	<1E-13
	Quade	2.57827E-03	3.65691E-03	3.65691E-03	3.65079E-03
NDE	Friedman	2.55436E-06	7.85957E-06	7.85957E-06	7.85955E-06
	Friedman Aligned	4.19953E-02	1.29854E-01	1.29854E-01	1.23666E-01
	Quade	1.60056E-01	5.02233E-01	5.02233E-01	4.15313E-01
TLBO	Friedman	1.57702E-01	4.05499E-01	4.05499E-01	3.53159E-01
	Friedman Aligned	6.48054E-01	1.0	1.0	9.29409E-01
	Quade	7.18467E-01	1.0	1.0	9.59945E-01
EBLSHADE	Friedman	9.13338E-01	1.0	9.23824E-01	9.89059E-01
	Friedman Aligned	8.67482E-01	1.0	1.0	9.76034E-01
	Quade	9.98363E-01	1.0	1.0	9.99993E-01
STLBO	Friedman	9.23824E-01	1.0	9.23824E-01	9.89059E-01
	Friedman Aligned	1.0	1.0	1.0	1.0
	Quade	1.0	1.0	1.0	1.0

Aligned, and Quade tests for the case of control algorithm ADELI and the task of R_{p1} evaluation. The reader is referred to the supplementary material for rest of p-values (Tables S4-S143).

As we can see in the table, the Finner tests exhibit the most powerful behavior, reaching the lowest p-values in the comparisons. The Friedman test shows a significant improvement in R_{p1} evaluation of ADELI over DE, NDE, MABC, GOTLBO, PSO, IJAYA, ISCA, NNA, CWOA, and WW for all the post-hoc procedures considered. The Friedman Aligned test only confirms the improvement of ADELI over the aforementioned 10 algorithms for every post-hoc procedure considered, except Holm, Hochberg, and Holland, which fail to highlight the differences between ADELI and NDE as significant.

3.3.2. *Evaluation of IV–set*

In the IV–set case, a comprehensive nonparametric statistical analysis of algorithms efficiency was performed on all parameters collected from all simulated curves. In this scenario, n had a value of 81:

$$n = 10\,T\,\text{values}\times(8\ \text{APE}_{\text{MEDIAN}}+1\ \text{RMSPE}_{\text{MEDIAN}})+1\ t_{\text{run}}\,.$$

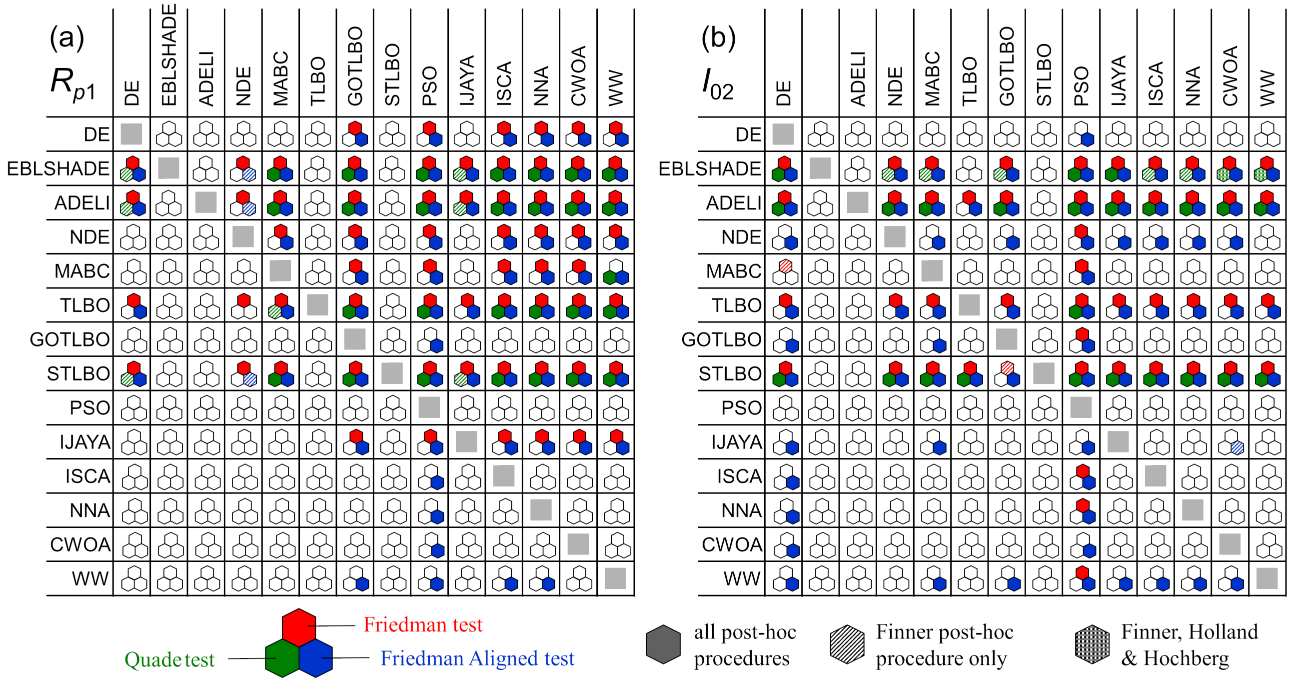

Figure 8: The results of algorithm comparison in R_{p1} (a) and I_{02} (b) evaluation by Friedman, Friedman Aligned, and Quade tests in the single–IV case. The colored hexagon indicates that the adjusted p-value, which tests the hypothesis that an algorithm in a row outperforms the algorithm in a column, is not greater than $p_{lim} = 0.1$. The solid fill signifies that every post-hoc procedure resulted in $p < p_{lim}$; the patterned fill indicates that only specific post-hoc procedures achieved this outcome. The correspondence between the color and position of the hexagon to a test as well as the fill pattern to procedures are shown in a legend at the bottom of the figure.

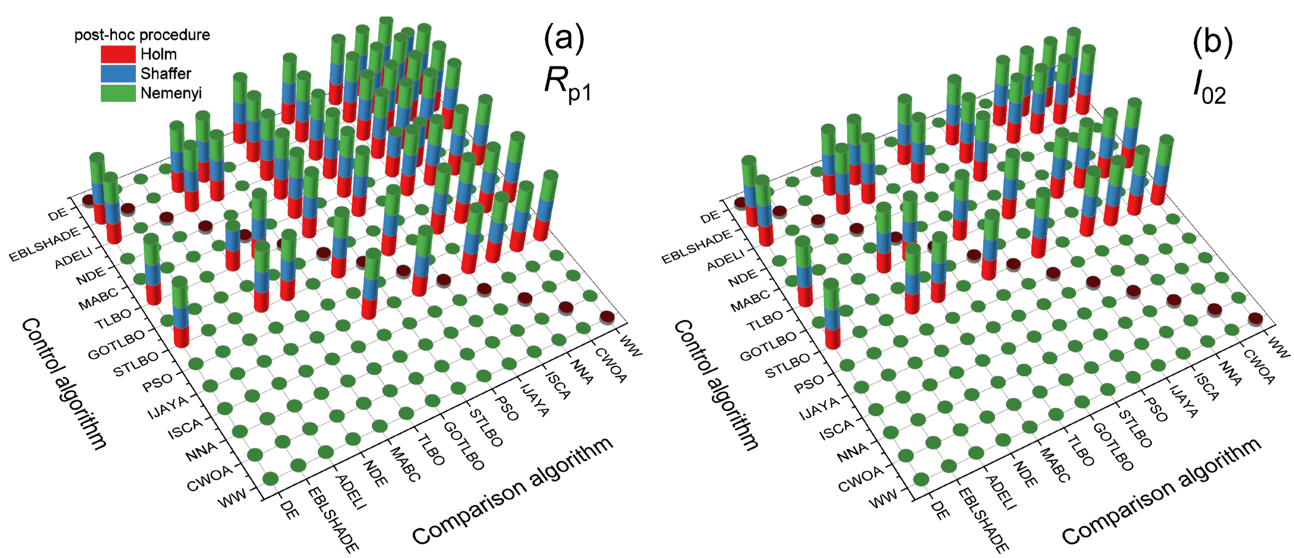

Figure 9: The results of multiple comparisons of R_{p1} (a) and I_{02} (b) evaluation among all algorithms in the single–IV case. The colored cylinder indicates that the adjusted p-value, which tests the control algorithm outperforms the comparison algorithm, is not greater than $p_{lim} = 0.1$. The correspondence between the color of the cylinder to a post-hoc procedure is shown in the figure legend.

4. Conclusion

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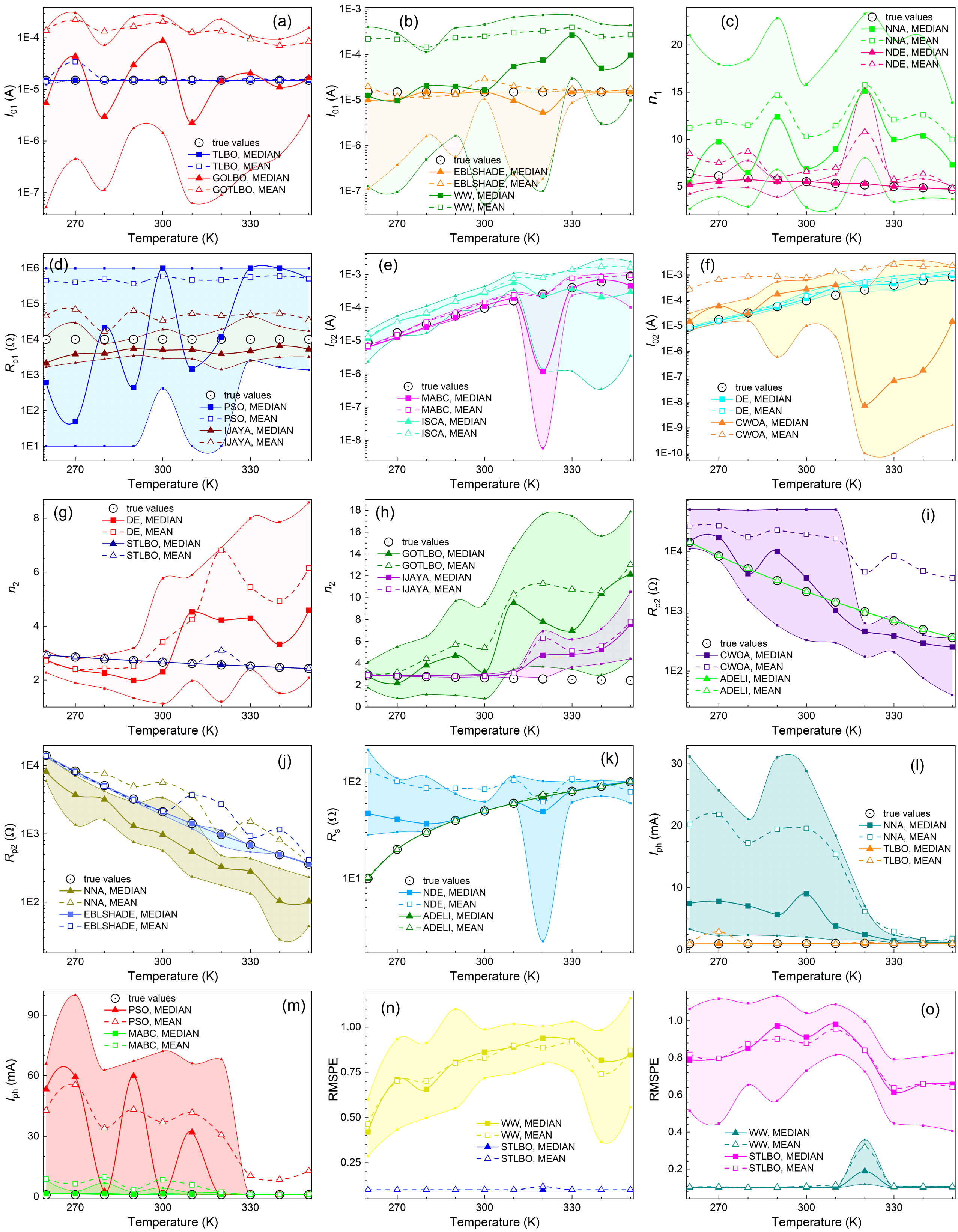

Figure 10: Dependences of the I_{01} (a, b), n_1 (c), R_{p1} (d), I_{02} (e, f), n_2 (g, h), R_{p2} (i, j), R_s (k), I_{ph} (l, m), and RMSPE (n, o) evaluation by different algorithm on the synthesis temperature. The IV-set is used. The circles represent the values, which have been used in IV curve simulations, the filled marks represent the median values, and the empty marks represent the mean values. The colored regions correspond to the IQR. The lines only serve as guide to the eye.

Table 4
Adjusted p-values for tests for multiple comparisons of I_{01} evaluation among all methods in the single–IV case ($p < 1.0$ are only shown).

Hypothesis	post-hoc procedure		
	Nemenyi	Holm	Shaffer
ADELI versus WW	<1E-13	<1E-13	<1E-13
ADELI versus NDE	1.17195E-12	1.15907E-12	1.00453E-12
STLBO versus CWOA	1.17195E-12	1.15907E-12	1.00453E-12
TLBO versus PSO	1.21236E-12	1.17240E-12	1.03917E-12
STLBO versus GOTLBO	1.21236E-12	1.17240E-12	1.03917E-12
ADELI versus DE	1.73772E-12	1.64224E-12	1.48948E-12
STLBO versus DE	1.83875E-12	1.71752E-12	1.57607E-12
ADELI versus CWOA	3.83915E-12	3.50164E-12	3.29070E-12
EBLSHADE versus GOTLBO	4.20286E-12	3.78719E-12	3.60245E-12
STLBO versus NDE	5.01110E-12	4.46043E-12	4.29523E-12
ADELI versus GOTLBO	5.41522E-12	4.76064E-12	4.64162E-12
EBLSHADE versus CWOA	5.98099E-12	5.19229E-12	5.12657E-12
EBLSHADE versus ISCA	1.17195E-11	1.00453E-11	1.00453E-11
EBLSHADE versus DE	1.45282E-11	1.22931E-11	1.06966E-11
EBLSHADE versus NDE	4.17053E-11	3.43725E-11	3.07061E-11
STLBO versus ISCA	8.17133E-11	6.64482E-11	6.01625E-11
TLBO versus WW	8.82197E-11	7.07696E-11	6.49529E-11
TLBO versus MABC	1.07900E-10	8.53717E-11	7.94431E-11
EBLSHADE versus MABC	3.09961E-10	2.38431E-10	2.28213E-10
ADELI versus NNA	3.24570E-10	2.46102E-10	2.38969E-10
ADELI versus ISCA	3.83410E-10	2.86504E-10	2.82291E-10
STLBO versus MABC	1.58351E-09	1.16588E-09	1.16588E-09
STLBO versus NNA	1.83408E-09	1.33021E-09	1.33021E-09
TLBO versus ISCA	3.49326E-09	2.49519E-09	2.22648E-09
ADELI versus MABC	5.83612E-09	4.10452E-09	3.71972E-09
EBLSHADE versus NNA	1.23520E-08	8.55140E-09	7.87272E-09
EBLSHADE versus PSO	1.47150E-08	1.00256E-08	9.37877E-09
STLBO versus PSO	5.32586E-08	3.57008E-08	3.39450E-08
ADELI versus PSO	1.50038E-07	9.89261E-08	.56286E-08
TLBO versus GOTLBO	2.16253E-07	1.40208E-07	1.37831E-07
EBLSHADE versus WW	2.39169E-07	1.52438E-07	1.52438E-07
TLBO versus CWOA	2.89034E-07	1.81043E-07	1.77867E-07
TLBO versus DE	5.91345E-07	3.63905E-07	3.63905E-07
STLBO versus WW	6.86296E-07	4.14794E-07	4.14794E-07
TLBO versus NDE	1.37158E-06	8.13904E-07	7.68687E-07
TLBO versus NNA	1.17758E-04	6.72904E-05	6.59964E-05
NNA versus WW	2.21281E-02	1.24015E-02	1.24015E-02
IJAYA versus WW	2.36193E-01	1.29777E-01	1.24585E-01
NNA versus PSO	2.36193E-01	1.29777E-01	1.24585E-01
NDE versus WW	4.04596E-01	2.13413E-01	2.13413E-01
DE versus WW	6.28685E-01	3.24706E-01	3.24706E-01
CWOA versus WW	8.94683E-01	4.52257E-01	4.52257E-01
GOTLBO versus WW	1.0	5.07626E-01	5.07626E-01
IJAYA versus PSO	1.0	8.15876E-01	7.97333E-01
NNA versus MABC	1.0	9.64793E-01	9.64793E-01

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Table 5
The results of Wilcoxon signed-rank test with a level of significance $\alpha = 0.05$ in the IV-set case. The "+" indicated that the null hypothesis was rejected, and the control algorithm (in the row) performed better then the comparison algorithm (in the column). The "0" indicates to rejection of the hypothesis about outperforming the control algorithm.

Control algorithm	Comparison algorithm DE	EBLSHADE	ADELI	NDE	MABC	TLBO	GOTLBO	STLBO	PSO	IJAYA	ISCA	NNA	CWOA	WW	Total (+/ = /−)
DE	■	0	0	0	+	0	+	0	+	0	+	+	+	+	7/0/6
EBLSHADE	+	■	0	+	+	0	+	0	+	+	+	+	+	+	10/0/3
ADELI	+	+	■	+	+	+	+	+	+	+	+	+	+	+	13/0/0
NDE	+	0	0	■	+	0	+	0	+	+	+	+	+	+	9/0/4
MABC	0	0	0	0	■	0	+	0	+	0	+	+	+	+	6/0/7
TLBO	+	+	0	+	+	■	+	0	+	+	+	+	+	+	11/1/1
GOTLBO	0	0	0	0	0	0	■	0	+	0	+	+	+	+	5/0/8
STLBO	+	+	0	+	+	0	+	■	+	+	+	+	+	+	11/1/1
PSO	0	0	0	0	0	0	0	0	■	0	0	0	0	0	0/4/9
IJAYA	+	0	0	0	+	0	+	0	+	■	+	+	+	+	8/0/5
ISCA	0	0	0	0	0	0	0	0	0	0	■	0	0	0	0/3/10
NNA	0	0	0	0	0	0	0	0	0	0	0	■	0	0	0/3/10
CWOA	0	0	0	0	0	0	0	0	0	0	0	0	■	0	0/4/9
WW	0	0	0	0	0	0	0	0	0	0	0	+	0	■	1/3/9

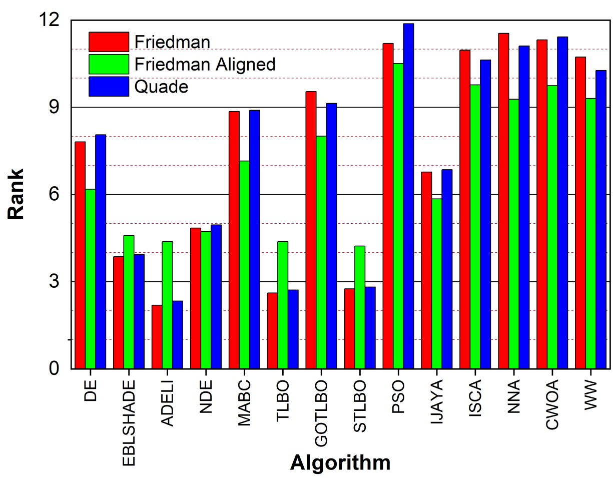

Figure 11: Ranking of the algorithms according to Friedman, Friedman Aligned, and Quade tests in the IV-set case.

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Table 6
Adjusted p-values for Friedman, Friedman Aligned, and Quade tests in IV–set case. STLBO is the control algorithm.

Algorithm	Test	post-hoc procedure Finner	Holm	Hochberg	Holland
GOTLBO	Friedman	<1E-13	<1E-13	<1E-13	<1E-13
	Friedman Aligned	1.35278E-10	5.09895E-10	5.09895E-10	5.09895E-10
	Quade	1.11445E-03	4.11614E-03	4.11614E-03	4.10873E-03
PSO	Friedman	<1E-13	<1E-13	<1E-13	<1E-13
	Friedman Aligned	<1E-13	<1E-13	<1E-13	<1E-13
	Quade	8.22938E-06	8.22941E-06	8.22941E-06	8.22938E-06
NNA	Friedman	<1E-13	<1E-13	<1E-13	<1E-13
	Friedman Aligned	<1E-13	<1E-13	<1E-13	<1E-13
	Quade	2.21284E-05	5.61727E-05	5.61727E-05	5.61713E-05
CWOA	Friedman	<1E-13	<1E-13	<1E-13	<1E-13
	Friedman Aligned	<1E-13	<1E-13	<1E-13	<1E-13
	Quade	1.48311E-05	2.73807E-05	2.73807E-05	2.73803E-05
DE	Friedman	2.32081E-13	8.03357E-13	8.03357E-13	8.03357E-13
	Friedman Aligned	1.74950E-09	6.45968E-09	6.45968E-09	6.45968E-09
	Quade	6.44257E-03	2.38175E-02	2.38175E-02	2.35824E-02
IJAYA	Friedman	2.17645E-10	8.03613E-10	8.03613E-10	8.03613E-10
	Friedman Aligned	3.63299E-09	1.25757E-08	1.25757E-08	1.25757E-08
	Quade	3.78757E-02	1.31885E-01	1.31885E-01	1.25109E-01
MABC	Friedman	1.75608E-09	6.61909E-09	6.61909E-09	6.61909E-09
	Friedman Aligned	<1E-13	<1E-13	<1E-13	<1E-13
	Quade	1.54776E-03	5.83595E-03	5.83595E-03	5.82137E-03
WW	Friedman	7.44635E-09	2.74942E-08	2.74942E-08	2.74942E-08
	Friedman Aligned	<1E-13	<1E-13	<1E-13	<1E-13
	Quade	1.10078E-04	3.81053E-04	3.81053E-04	3.80989E-04
ISCA	Friedman	1.32325E-08	4.58048E-08	4.58048E-08	4.58048E-08
	Friedman Aligned	<1E-13	<1E-13	<1E-13	<1E-13
	Quade	5.64886E-05	1.73815E-04	1.73815E-04	1.73801E-04
NDE	Friedman	9.57698E-04	2.94709E-03	2.94709E-03	2.94383E-03
	Friedman Aligned	2.69373E-03	8.29097E-03	8.29097E-03	8.26522E-03
	Quade	2.98714E-01	9.55486E-01	9.55486E-01	6.64392E-01
EBLSHADE	Friedman	8.62842E-02	2.20533E-01	2.20533E-01	2.04719E-01
	Friedman Aligned	3.10807E-02	7.90881E-02	7.90881E-02	7.70214E-02
	Quade	5.99120E-01	1.0	1.0	9.01765E-01
ADELI	Friedman	1.0	1.0	1.0	1.0
	Friedman Aligned	3.64522E-01	6.83937E-01	3.45600E-01	5.66995E-01
	Quade	1.0	1.0	1.0	1.0
TLBO	Friedman	1.0	1.0	1.0	1.0
	Friedman Aligned	3.64522E-01	6.83937E-01	3.45600E-01	5.66995E-01
	Quade	1.0	1.0	1.0	1.0

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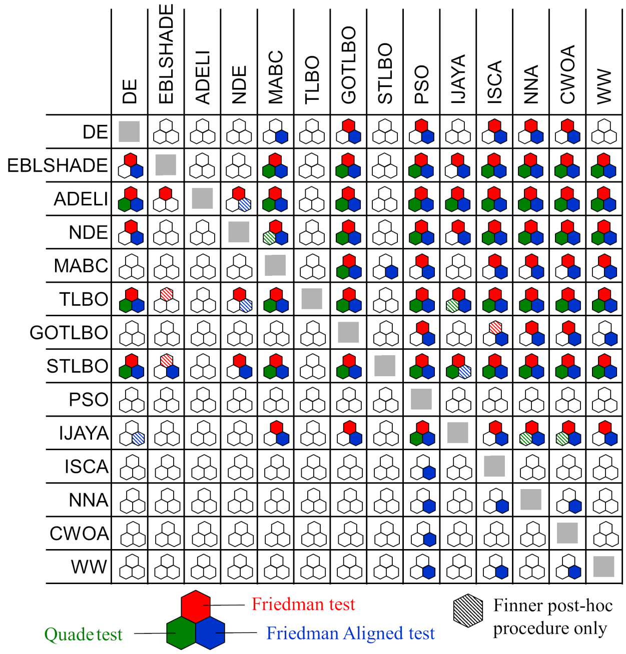

Figure 12: The results of algorithm comparison by Friedman, Friedman Aligned, and Quade tests in the IV-set case. The colored hexagon indicates that the adjusted p-value, which tests the hypothesis that an algorithm in a row outperforms the algorithm in a column, is not greater than $p_{lim} = 0.1$. The solid fill signifies that every post-hoc procedure resulted in $p < p_{lim}$; the dashed fill indicates that the Finner post-hoc procedure was the only method that produced this result. The correspondence between the color and position of the hexagon to a test is shown in a legend at the bottom of the figure.

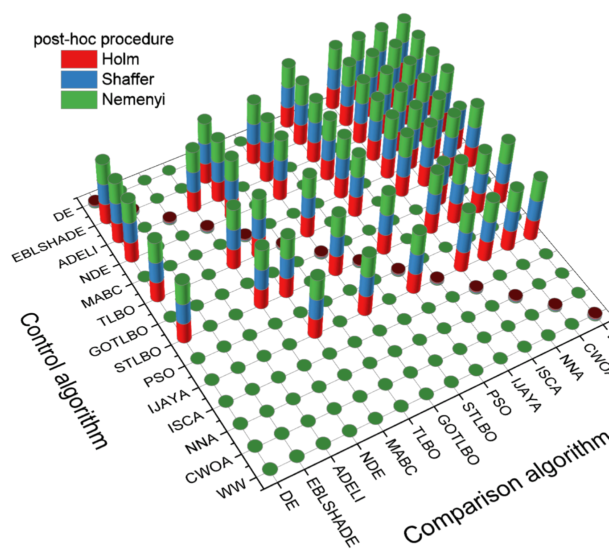

Figure 13: The results of multiple comparisons among all algorithms in the IV-set case. The colored cylinder indicates that the adjusted p-value, which tests the control algorithm outperforms the comparison algorithm, is not greater than $p_{lim} = 0.1$. The correspondence between the color of the cylinder to a post-hoc procedure is shown in the figure legend.

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Table 7
Adjusted p-values for tests for multiple comparisons among all methods in the IV–set case ($p < p_{lim}$ are only shown).

Hypothesis	post-hoc procedure Nemenyi	Holm	Shaffer
EBLSHADE versus WW, ADELI versus MABC, ADELI versus PSO, ADELI versus ISCA, ADELI versus NNA, ADELI versus CWOA, ADELI versus WW, NDE versus NNA, TLBO versus GOTLBO, TLBO versus PSO, TLBO versus ISCA, TLBO versus NNA, TLBO versus CWOA, STLBO versus GOTLBO, STLBO versus PSO, STLBO versus NNA, STLBO versus CWOA	<1E-13	<1E-13	<1E-13
IJAYA versus NNA	1.61648E-12	1.31450E-12	1.19016E-12
EBLSHADE versus MABC	3.75833E-12	3.01492E-12	2.76712E-12
NDE versus GOTLBO	4.20286E-12	3.32534E-12	3.09441E-12
STLBO versus DE	8.12284E-12	6.33760E-12	5.98055E-12
IJAYA versus CWOA	2.31157E-11	1.75273E-11	1.70193E-11
TLBO versus DE	4.02505E-11	3.00773E-11	2.96350E-11
IJAYA versus PSO	9.52918E-11	7.01599E-11	7.01599E-11
IJAYA versus ISCA	1.29115E-09	9.36436E-10	9.36436E-10
ADELI versus DE	2.22329E-09	1.56363E-09	1.41704E-09
EBLSHADE versus GOTLBO	3.53238E-09	2.44550E-09	2.25141E-09
NDE versus MABC	9.68759E-09	6.49388E-09	6.17451E-09
IJAYA versus WW	1.72440E-08	1.13697E-08	1.09907E-08
NDE versus WW	1.75252E-08	1.13697E-08	1.11699E-08
EBLSHADE versus DE	1.82602E-08	1.16384E-08	1.16384E-08
EBLSHADE versus ISCA	1.88327E-08	1.17963E-08	1.16384E-08
EBLSHADE versus PSO	4.78066E-08	2.94194E-08	2.94194E-08
ADELI versus GOTLBO	4.98663E-08	3.01390E-08	3.01390E-08
EBLSHADE versus CWOA	7.52618E-08	4.46609E-08	4.21797E-08
STLBO versus MABC	8.60481E-08	5.01159E-08	4.82248E-08
NDE versus ISCA	9.60138E-08	5.48650E-08	5.38099E-08
DE versus NNA	1.60867E-07	9.01562E-08	9.01562E-08
EBLSHADE versus NNA	1.68788E-07	9.27404E-08	9.01562E-08
TLBO versus MABC	2.16163E-07	1.16396E-07	1.14020E-07
NDE versus PSO	4.07575E-07	2.14985E-07	2.14985E-07
STLBO versus WW	4.16995E-07	2.15371E-07	2.15371E-07
TLBO versus WW	6.32636E-07	3.19794E-07	3.19794E-07
NDE versus CWOA	8.17751E-07	4.04382E-07	4.04382E-07
STLBO versus ISCA	8.33647E-07	4.04382E-07	4.04382E-07
DE versus CWOA	1.47836E-06	6.98567E-07	6.98567E-07
DE versus PSO	4.48549E-06	2.07023E-06	2.07023E-06
DE versus ISCA	3.33823E-05	1.50404E-05	1.46735E-05
NDE versus DE	1.56228E-04	6.86718E-05	6.86718E-05
DE versus WW	2.41908E-04	1.03675E-04	1.03675E-04
IJAYA versus GOTLBO	7.27786E-04	2.95913E-04	2.95913E-04
MABC versus NNA	1.28945E-03	5.10114E-04	5.10114E-04
ADELI versus NDE	1.70688E-03	6.56493E-04	6.56493E-04
MABC versus CWOA	6.56486E-03	2.45281E-03	2.45281E-03
MABC versus PSO	1.46075E-02	5.29723E-03	5.13671E-03
TLBO versus NDE	2.83112E-02	9.95560E-03	9.95560E-03
MABC versus ISCA	6.08528E-02	2.07301E-02	2.07301E-02
STLBO versus NDE	6.70463E-02	2.21032E-02	2.21032E-02
IJAYA versus MABC	6.92376E-02	2.21032E-02	2.21032E-02
GOTLBO versus NNA	1.07776E-01	3.31618E-02	3.31618E-02
MABC versus WW	2.35963E-01	6.74180E-02	6.74180E-02