2023 IEEE Symposium Series on Computational Intelligence (SSCI)
Mexico City, Mexico. December 5-8, 2023

Insights into the 2022 WCCI-GECCO Competition: Statistical Analysis of Evolutionary Computation in the Energy Domain

Fernando Lezama, José Almeida, João Soares, Bruno Canizes and Zita Vale
GECAD
LASI - Polytechnic of Porto
Porto, Portugal
{flz,jorga,jan,bmc,zav}@isep.ipp.pt

***Abstract*—In the energy field, the "WCCI(CEC)/GECCO Competition Evolutionary Computation in the Energy Domain: Risk-based Energy Scheduling" is a platform for testing and comparing new evolutionary algorithms (EAs) to address complex energy problems. Nonetheless, the current competition ranking metric is not statistically significant in assessing algorithm performance and only considers the mean fitness value associated with the objective function. Thus, this work undertakes a statistical analysis using the Shapiro-Wilks test, the Wilcoxon pair-wise comparison, and the Kruskal-Wallis technique to comprehensively study algorithm performance based on statistical grounds. The results reveal that, according to the Wilcoxon test, the top three algorithms demonstrate significant superiority over the other algorithms. In contrast, the Kruskal-Wallis test shows that the top four algorithms belong to the same group based on the ranks resulting from the test. This rigorous analysis provides valuable insights into the stochastic performance of algorithms, contributing to a deeper understanding of their capabilities in the context of the competition.**

***Index Terms*—Energy resource management, Evolutionary computation, Optimization, Statistical analysis, Smart grid**

I. Introduction

Power and energy systems have become complex environments due to the continued development of the electrical grid, which includes the integration of smart grid (SG) technologies and the rising penetration of distributed generators (DGs) and new resources such as electric vehicles and energy storage systems [1], [2]. This paradigm shift in the energy field has led utilities, governments, and research centers to look for innovative approaches to address the challenges posed by this complex dynamic environment [3], [4]. Accounting for the uncertainty associated with stochastic renewable generation presents difficulties in formulating optimization problems, making real-world solutions unrealistic without significant assumptions and simplifications [5].

In response to the complexities in the energy domain and to attract research centers' interest in tackling these issues, worldwide competitions held at major events and conferences have emerged as viable alternatives. Among these initiatives is the "2022 WCCI(CEC)-GECCO Competition on Evolutionary Computation in the Energy Domain: Risk-based Energy Scheduling" [6], which has gained recognition as a relevant platform for testing and comparing cutting-edge computational intelligence (CI) algorithms. This article introduces the benchmark launched during the competition, continuing the tradition of fostering cutting-edge solutions for complex energy problems.

In this 2022 edition, the organizers proposed a test bed focusing on optimizing aggregators' risk-based day-ahead energy resource management (ERM) [7]. This complex energy domain problem considers uncertainties arising from the significant integration of distributed energy resources (DERs) [8]. The test bed follows the same framework of previous competitions, allowing former participants to easily adapt their algorithms to this new test bed [6]. The problem, in turn, involves a centralized day-ahead ERM scenario within a smart grid operating in a 13-bus distribution network. A case study with 15 scenarios is used, with three being extreme occurrences with a substantial influence on the value of the objective function, even with a low probability of occurring. To assess the risk associated with these extreme events, a conditional value-at-risk (CVaR) mechanism is employed with a confidence level (α) of 95%, a typical value in the literature for economics [9], [10]. The proposed track has been constructed using the same framework as prior competitions. Still, several changes have been made to improve its efficacy and prevent algorithm initialization heuristics from being tweaked.

The paper is structured as follows: after this introduction section, section II describes the competition track regarding the proposed ERM problem. In section III, we show the MATLAB implementation of the simulation framework and the participants' algorithms and affiliations. The statistical analysis of the competition results is made in section IV, and the drawn conclusions are presented in the last section.

II. Competition schedule and test bed

The 2022 Competition on "Evolutionary Computation in the Energy Domain: Risk-based Energy Scheduling" was launched at prestigious events, including the IEEE World Congress Computational Intelligence (WCCI) and

This work has received funding from FEDER Funds through COMPETE program and from National Funds through (FCT) under the project UIDB/00760/2020. José Almeida is supported by FCT with Ph.D. Grant 2022.09590.BD. João Soares has received funding from FCT, namely CEECIND/00420/2022.

the ACM Genetic and Evolutionary Computation Conference (GECCO). Its primary goal is to converge and assess cutting-edge algorithms implemented for complex problems in the energy sector. These innovative approaches have attracted significant interest among practitioners because they can tackle the intricacies of mathematical problems characterized by high-dimensionality, non-linearity, non-convexity, multimodality, and discontinuity within the search space [5]. However, following the "no-free lunch theorem" [11] stating that there is no one algorithm that performs best for every problem, we have created a cohesive simulation framework that enables users to test computational intelligence (CI) metaheuristics solving real-world problems, surpassing conventional and standardized benchmarks.

The 2022 competition introduces one single test bed (the 2021 edition had two) and received support from esteemed organizations, including the IEEE CIS (Computational Intelligence Society), the IEEE WGMHO (Working Group on Modern Heuristic Optimization), and the IEEE ISATC (Intelligent System Application Technical Committee) Task Force 3 on Computational Intelligence in the Energy Domain. To account for the uncertainty from the high penetration of distributed energy resources (DER), the test bed replicates the risk-based optimization problem surrounding aggregators' day-ahead energy resource management (ERM).

Detailed guidelines, rules, and the conference schedule are available at "http://www.gecad.isep.ipp.pt/ERM-competitions/2022-2/." The website also provides access to the simulation framework and algorithms used during the competition, presenting an open challenge for CI practitioners interested in tackling these complex problems. The MATLAB© software was used to develop and test the competition's platform. The competition timeline, along with significant occasions where results were taken into account and presented, are as follows:

- 01/01/2022: First call to competitors.
- 02/21/2021: Open submissions for Special Session 44 on EA for complex optimization in the energy domain at CEC 2022.
- 04/11/2022: Open submission for short papers to GECCO 2022.
- 30/06/2022: Deadline for Submitting results and codes to the organizers.
- 09-13/07/2022: Announcement of the winner algorithms at GECCO 2022.
- 18-23/07/2022: Announcement of the winner algorithms at WCCI 2022.
- 03 August 2022: Final results have been published on the competition site.

In the proposed test bed, we address the ERM problem while accounting for uncertainty in market pricing, renewable energy production, load consumption, and electric vehicle travels. This problem was originally proposed in previous works [12]. We consider several scenarios with a corresponding probability of occurrence to fully portray these parameters' stochastic character. This new test bed's innovation lies in incorporating risk strategies into the formulation, which enables the aggregator to plan its operation while taking into account various levels of risk associated with various scenarios, including risk-neutral and risk-averse concerns [13].

In summary, the new proposed test bed considers the following key aspects:

- A day-ahead ERM model that considers uncertainties in market pricing, renewable energy production, load consumption, and electric vehicle travels.
- The use of risk analysis approaches that address parameter uncertainty and produce solutions that protect the aggregator from extreme events using tools like Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR).
- Participants will implement solution methods based on modern metaheuristic optimization techniques to handle the computational demand posed by numerous possible scenarios of uncertain parameters and the large number of variables considered.
- Utilizing realistic data from power and energy systems, the outcomes will enable us to evaluate the impact of VaR and CVaR metrics across various scenarios.

The suggested test bed is shown in Figure 1. The VaR and CVaR values are calculated based on the expected cost, the cost of each scenario, and their respective probabilities, following the formulation in [7]. The aggregator then engages in a decision-making process impacted by the risk aversion element. The optimal strategy is chosen by evaluating the objective function (OF) based on these risk measures.

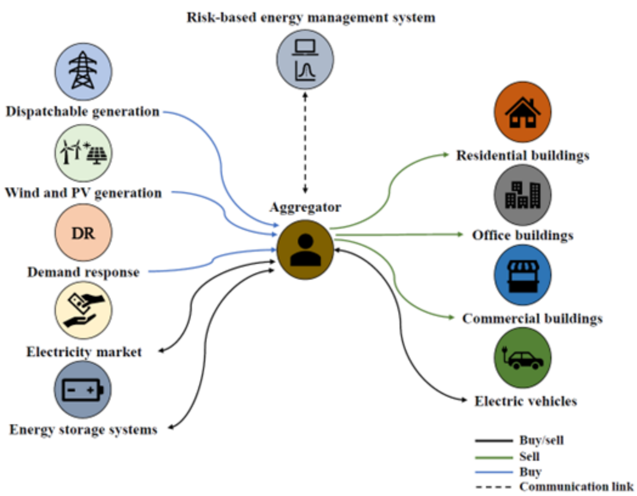

Fig. 1. Representation of the considered risk-based ERM problem.

Within a set number of iterations, the metaheuristic seeks to reduce the value of the OF. When $\beta = 0$, the metaheuristic minimizes the expected cost. On the other hand, when $\beta = 1$, the metaheuristic aims to minimize both the expected cost and the $CVaR_{\alpha}$, as described in [13].

The aggregator's schedule is created based on the expected scenario without considering risk. The expected cost, whose formulation is as follows, determines the cost and value of the OF without a risk aversion strategy:

$$z_s^{\text{tot}} = z_s^{\text{OC}} - z_s^{\text{In}} + P_s \quad (1)$$

$$z^{\text{Ex}} = \sum_{s=1}^{N_s} (\rho_s \cdot z_s^{\text{tot}}) \quad (2)$$

The total objective function (OF) value of each scenario s, denoted as z_s^{tot}, is determined by the difference between operational costs (z_s^{OC}) and income (z_s^{In}) in that scenario, along with the penalty for any variable bound violations (P_s). The expected OF cost, z^{Ex}, is computed considering the probabilities ρ_s of the respective scenarios.

Incorporating a risk-aversion strategy accounts for the uncertainty associated with the aforementioned technologies. An additional cost, $CVaR_\alpha$, is added to the scenarios with the highest costs. The calculation is determined using the following formulation [7]:

$$CVaR_\alpha(z_s^{\text{tot}}) = VaR_\alpha(z_s^{\text{tot}}) + \frac{1}{1-\alpha} \sum_{s=1}^{N_s} (\rho_s \cdot \varphi) \quad (3)$$

where:

$$\varphi = \begin{cases} z_s^{\text{tot}} - z^{\text{Ex}} - VaR_\alpha(z_s^{\text{tot}}), & \text{if } z_s^{\text{tot}} \geq z^{\text{Ex}} + VaR_\alpha(z_s^{\text{tot}}) \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

$$VaR_\alpha(z_s^{\text{tot}}) = zscore(\alpha) \cdot std(z_s^{\text{tot}}) \quad (5)$$

where φ represents a parameter associated with the cost in the worst-case scenarios, where each scenario s exceeds the expected cost, including the VaR_α value. On the other hand, when the cost is lower than the expected cost, φ is set to 0. The z-score is calculated using MATLAB's norminv() function with a confidence level of α = 95%.

When considering this parameter, the scheduling problem's fitness value (and OF value) differs according to the degree of risk aversion. According to this risk-aversion instance, the fitness value (or OF) model is represented as follows:

$$OF = z^{\text{Ex}} + \beta \cdot CVaR_\alpha(z_s^{\text{tot}}) \quad (6)$$

For this problem, the parameter β represents the degree of aversion to risk, expressed as a percentage. This parameter takes values between 0 and 1. A β value of 0 represents a risk-neutral strategy where the OF value equals the expected cost. On the other hand, a β value of 1 implies a 100% aversion to risk, yielding the safest solution in response to worst-case scenarios.

For the 2022 competition, a default setting of β = 1 is established. The equations for operational costs (z_s^{OC}) and incomes (z_s^{In}) are provided in [7], offering a comprehensive insight into these aspects of the problem formulation.

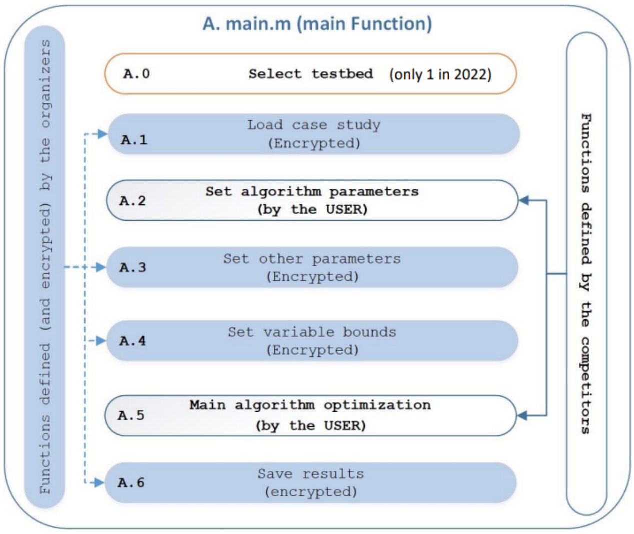

Fig. 2. Implemented simulation framework platform.

III. Implemented Platform and Participants

In line with past editions of these competitions, the authors provide a user-friendly platform to facilitate participants in implementing their algorithms. As a reference approach, the authors offer a sample algorithm, the HyDE algorithm [14]. The simulation framework follows the structure illustrated in Figure 2.

The organizers have created a simulation platform implemented in MATLAB© 2018 64-bit, comprising various scripts that serve different functions during the simulation process. The organizers use specific scripts to handle activities, including loading the case study depending on the chosen test bed, establishing parameters and variable bounds, and automatically storing participant outcomes. These scripts are marked in blue in Figure 2. The goal is to prevent participants from changing the case studies and approach the problems as black-box optimization functions.

To participate, each participant needs to implement two scripts: i) A.2 script to set the parameters their algorithm requires. ii) A.6 script to implement their proposed solution method.

The organizer's script's platform functionality and comprehensive instructions on implementing these two script functions are supplied in [6], Sect. 4. details on how the solutions should be encoded, the assumptions made, and the competition's evaluation procedure provided in the guidelines document [6]. An essential parameter is the maximum number of function evaluations for each trial. For the 2022 test bed, participants are restricted to 5,000 function evaluations per trial. Participants must consider this constraint when designing their algorithms, as the number of function evaluations may vary from algorithm to algorithm.

The competition got 15 entries from a diverse range of countries. Table I shows the participants and the obtained positions (showing with bold font the winners). Notice that some entries present a N/A position (in the RI column), meaning those entries were disqualified after the validation process of the organizing committee. The validation process was quite straightforward, allowing the organizers to confirm if the results provided were, in fact, valid. To do so, the organizers modified the position of some variables in the encoding of the solutions. Such changes in the positions of variables should not supposedly affect the performance of the algorithms (as it was verified for most participants); however, participants taking advantage of the knowledge of the structure of the solution and setting some position to a fixed value were highly penalized with such a change. With this easy test, the authors were able to find anomaly entries and, at the same time, verify the generality of the optimizers submitted.

IV. Statistical analysis

The ranking index, which represents the fitness function's average value across 20 requested trials, has been used in this competition's evaluation:

$$\mathrm{RI}_{(a)}^{\mathrm{user}} = \frac{1}{N^{\mathrm{trials}}} \sum_{i=1}^{N^{\mathrm{trials}}} (\mathrm{Fit}_a(\vec{X}_i)) \tag{7}$$

where $\mathrm{RI}_{(a)}^{\mathrm{user}}$ is and index used to rank the participant a; N^{trials} is the number of runs; $\mathrm{Fit}_a(\vec{X}_i)$ computes the fitness of solution $\vec{X}_i$. Thus, the ranking index corresponds to the average fitness value obtained in the 20 trials.

This method makes it easier to evaluate the performance of algorithms and guarantees that the winning algorithm has a better overall fitness for a specific test bed. A stronger average fitness does not, however, indubitably imply a statistically superior algorithm performance within a specific confidence interval because of the stochastic nature of optimizers.

For instance, Fig. 3 shows the boxplot of the final fitness value obtained by the optimizers. Notice that, apart from the high costly values of PSO, ABC-DE, GA-PSO, and DE-TLBO, no further conclusions about the performance of the algorithms can be drawn based exclusively on the fitness value. Notice that in the figure, US and DRL_DE were not included. In the following tables (Table II and Table III), they appear as N/A since these algorithms were disqualified for not following the competition guidelines.

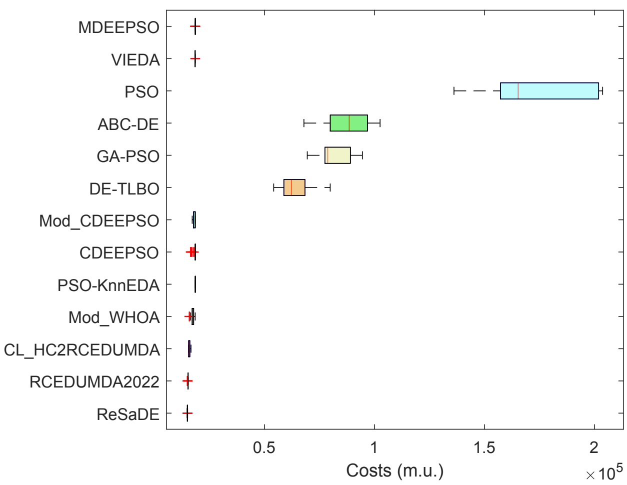

Fig. 3. Final fitness solution for each algorithm over the 20 trials.

Thus, an alternative approach to assess the performance of EAs is based on using statistical tools for group and pairwise comparisons. Such comparisons involve straightforward statistical tests applied within the framework proposed in this study. The validation of the performance of algorithms using statistical tools provides further insights to be discussed and analyzed, and the different tables and results obtained with it serve as valuable and more reliable proof of the performance of stochastic optimizers.

To extend the analysis of results, we perform a Shapiro-Wilks test for a significance level of 5% [15]. This test takes the final fitness values for each metaheuristic over the 20 runs as input and tests if the fitness values follow a normal distribution with unspecified mean and standard deviation. The test assesses the normality of data and determines whether parametric statistical methods that assume normality can be applied to the results. If the data deviates significantly from a normal distribution, alternative non-parametric methods might be required. Table II shows the results obtained from this statistical analysis. It can be noticed that Mod_WHOA, DE-TLBO, GA-PSO, and ABC-DE are the only ones that accept the null hypothesis of the test since their p-value is greater than 0.05. This means that the results of the remaining algorithms do not follow a normal distribution, rejecting the test's null hypothesis. As such, non-parametric tests must be used for multiple or pairwise comparisons.

Having obtained the results of the Shapiro-Wilks, the statistical analysis continues with the Wilcoxon signed-rank test [16]. The Wilcoxon test is a non-parametric procedure used to analyze whether two samples represent different populations, effectively detecting significant differences in the performance or behavior of the two algorithms [17]. The results from the Wilcoxon test, as shown in Table III, provide comprehensive insights into the algorithms' performance, having as a reference the announced winners. It is evident that ReSaDE stands out as the competition winner with a much better performance than other participants. RCEDUMDA2022 [18] exhibits significant superiority over all other algorithms (except ReSaDE), and CL-HC2RCEDUMDA does the same, being statistically superior to the rest of the algorithms (except the first and second positions).

Overall, the Wilcoxon test outcomes provide valuable statistical evidence regarding the relative performances of the algorithms in comparison to the announced winners.

Finally, we use a non-parametric pairwise comparison based on the Kruskal-Wallis statistical test [19]. The Kruskal-Wallis test is a non-parametric statistical test used to compare the medians of two or more independent groups in a dataset. The Kruskal-Wallis test ranks all the data values from lowest to highest across all the groups. Then, the ranks are used to calculate a test statistic, which measures the differences between the group medians. If the test statistic is large enough, it suggests significant differences in medians among the groups. Figure 4 shows graphically the group means obtained by the test. It can be noticed that nine groups (in red color in the figure) present a significantly worse mean rank compared to the winner ReSaDE. In grey color, we can see that the

TABLE I

THE 2022 EDITION OF THE COMPETITION RECEIVED 15 SUBMISSIONS. THE TEAMS CAME FROM DIFFERENT COUNTRIES WITH APPROACHES OF DIFFERENT TYPES (CLASSICAL AND HYBRID ALGORITHMS).

ID	Algorithm	Main Affiliation	Country	RI
1	Particle Swarm Optimization with Knn Estimation of Distribution Algorithm (PSO-KnnEDA)	South China University of Technology	China	8th
2	Univariate Search (US)	University of Chinese Academy of Sciences	China	N/A
3	Canonical Differential Evolutionary Particle Swarm Optimization (C-DEEPSO)	Federal University of Rio de Janeiro; University of Alcalá	Brazil; Spain	6th
4	Dimensionality Reduction DE with Local Reconstruction of Population (DRL_DE)	Nankai University	China	N/A
5	Ring Cellular Encode-Decode Univariate Marginal Distribution Algorithm (RCE-DUMDA2022)	Unidad de Transferencia Tecnológica Tepic del Centro de Investigación Científica y de Educación Superior de Ensenada; Consejo Nacional de Ciencia y Tecnología; Universidad de Camagüey	Mexico; Cuba	**2nd**
6	Modified C-DEEPSO with Local Search Operators (C-DEEPSO_Mod)	Federal University of Rio de Janeiro; University of Alcalá	Brazil; Spain	5th
7	Differential Evolution-Teaching Learning Based Optimization (DE-TLBO)	Sardar Vallabhbhai National Institute of Technology	India	10th
8	Genetic Algorithm-Particle Swarm Optimization (GA-PSO)	Sardar Vallabhbhai National Institute of Technology	India	11th
9	Artificial Bee Colony (ABC)	Sardar Vallabhbhai National Institute of Technology	India	12th
10	Restart-Assisted Self-Adaptive Differential Evolution (ReSaDE)	Alibaba DAMO Academy	China	**1st**
11	Particle Swarm Optimization (PSO)	Sao Paulo State University	Brazil	13th
12	Chaotic Levy Hill-Climbing to RCEDUMDA (CL_HC2RCEDUMDA)	Chandubhai S. Patel Institute of Technology	India	**3rd**
13	Modified Wild Horse Optimizer (Mod_WHO)	University of Salamanca	Spain; Brazil; Portugal	4th
14	Vortex Island Estimation of Distribution Algorithm (VIEDA)	University of Camaguey	Cuba; Mexico	7th
15	Modified Differential Evolutionary Particle Swarm Optimization (MDEEPSO)	National University of Colombia	Colombia	9th

TABLE II

SHAPIRO-WILKS STATISTICAL TEST FOR EACH ALGORITHM OVER 20 TRIALS.

	W	p-value	H
ReSaDE	0.70138	0.0001	1-Reject
RCEDUMDA2022	0.68697	0.0001	1-Reject
CL_HC2RCEDUMDA	0.76693	0.0003	1-Reject
Mod_WHOA	0.94686	0.3219	0-Accept
PSO-KnnEDA	0.64587	0.0000	1-Reject
CDEEPSO	0.51360	0.0000	1-Reject
Mod_CDEEPSO	0.75810	0.0002	1-Reject
DE-TLBO	0.94085	0.2143	0-Accept
GA-PSO	0.91846	0.0926	0-Accept
ABC-DE	0.95557	0.4595	0-Accept
PSO	0.85205	0.0058	1-Reject
VIEDA	0.81273	0.0022	1-Reject
MDEEPSO	0.61241	0.0000	1-Reject
US	N/A	N/A	N/A
DRL_DE	N/A	N/A	N/A

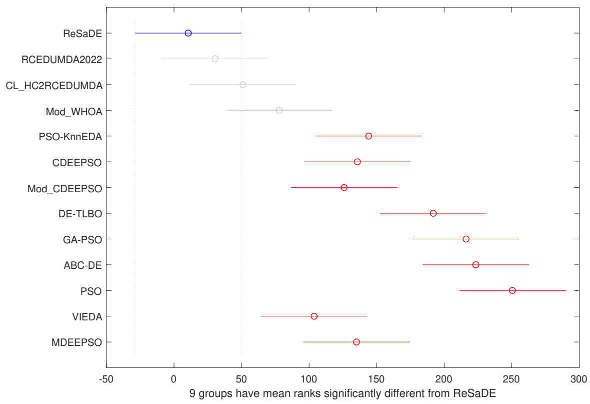

Fig. 4. Pairwise comparison amongst algorithms from Kruskal-Wallis statistical test for each algorithm over 20 trials.

mean ranks of RCEDUMDA2022, CL_HC2RCEDUMDA, and Mod_WHOA belong to the same group of ReSaDE, meaning that according to this test, those algorithms are not significantly different, even though ReSaDE achieved a lower mean rank.

V. CONCLUSIONS

The launched competition, targeting a problem in the energy domain serves as a valuable platform for testing and comparing new Evolutionary Algorithms (EAs) in addressing complex energy problems. The announced winners, ReSaDE (first place), RCEDUMDA2022 (second

TABLE III

SIGNED-RANK WILCOXON STATISTICAL TEST FOR ALL PARTICIPANTS OVER 20 TRIALS.

	ReSaDE (1st)	**RCEDUMDA2022 (2nd)**	**CL-HC2RCEDUMDA (3rd)**	**RI (position)**
PSO-KnnEDA	'+'	'+'	'+'	18,543 (8th)
US	N/A	N/A	N/A	N/A
C-DEEPSO	'+'	'+'	'+'	18,233 (6th)
DRL_DE	N/A	N/A	N/A	N/A
RCEDUMDA2022	'+'	'='	'-'	**15,255 (2nd)**
C-DEEPSO_Mod	'+'	'+'	'+'	18,115 (5th)
DE-TLBO	'+'	'+'	'+'	63,365 (10th)
GA-PSO	'+'	'+'	'+'	81,440 (11th)
ABC	'+'	'+'	'+'	87,749 (12th)
ReSaDE	'='	'-'	'-'	**14,951 (1st)**
PSO	'+'	'+'	'+'	173,796 (13th)
CL_HC2RCEDUMDA	'+'	'+'	'='	**15,777 (3rd)**
Mod-WHO	'+'	'+'	'+'	17,387 (4th)
VIEDA	'+'	'+'	'+'	18,494 (7th)
MDEEPSO	'+'	'+'	'+'	18,545 (9th)

place), and CL_HC2RCEDUMDA (third place), demonstrated statistically significant superiority over the other participants. The ranking index effectively captured the clear distinctions in performance for these top-performing algorithms. However, when considering the Kruskal-Wallis statistical test, it was determined that RCEDUMDA2022 (second place), CL_HC2RCEDUMDA (third place), and even Mod_WHOA (fourth place) belong to the same ReSaDE (winner) group. Thus, the statistical significance of their differences was less conclusive. In any case, the Wilcoxon test determined a statistical difference between the top-three algorithms and the rest of the participants.

To enhance the evaluation process in future competition editions, it is suggested to incorporate additional statistical metrics that offer more nuanced insights. These improvements will ensure a more comprehensive assessment of algorithm performance and contribute to advancing the field of evolutionary computation in the energy domain. For future work, it is recommended to explore the use of statistical tests and to increase the number of trials, possibly to at least 100, to better ascertain the true performance differences. Also, comparison with other algorithms, such as the winners of previous editions [20], is worth studying for similar test beds in the future.

REFERENCES

[1] GJRE Dileep. A survey on smart grid technologies and applications. *Renewable energy*, 146:2589–2625, 2020.

[2] José Almeida, João Soares, Bruno Canizes, and Zita Vale. Coordination strategies in distribution network considering multiple aggregators and high penetration of electric vehicles. *Procedia Computer Science*, 186:698–705, 2021.

[3] Steffen Limmer, Fernando Lezama, João Soares, and Zita Vale. Coordination of home appliances for demand response: An improved optimization model and approach. *IEEE Access*, 9:146183–146194, 2021.

[4] Yongli Wang, Yudong Wang, Yujing Huang, Jiale Yang, Yuze Ma, Haiyang Yu, Ming Zeng, Fuwei Zhang, and Yanfu Zhang. Operation optimization of regional integrated energy system based on the modeling of electricity-thermal-natural gas network. *Applied Energy*, 251:113410, 2019.

[5] João Soares, Tiago Pinto, Fernando Lezama, and Hugo Morais. Survey on Complex Optimization and Simulation for the New Power Systems Paradigm. *Complexity*, 2018:1–32, August 2018.

[6] João Soares, Fernando Lezama, Jose Alemeida, Bruno Canizes, and Zita Vale. Guidelines for WCCI(CEC)/GECCO 2022 Competition Evolutionary Computation in the Energy Domain: Risk- based Energy Scheduling. 2022.

[7] Jose Almeida, Joao Soares, Fernando Lezama, and Zita Vale. Robust Energy Resource Management Incorporating Risk Analysis Using Conditional Value-at-Risk. *IEEE Access*, 10:16063–16077, 2022.

[8] Seyed Mohsen Hosseini, Raffaele Carli, and Mariagrazia Dotoli. Robust Optimal Energy Management of a Residential Microgrid Under Uncertainties on Demand and Renewable Power Generation. *IEEE Transactions on Automation Science and Engineering*, 18(2):618–637, April 2021.

[9] Sergey Sarykalin, Gaia Serraino, and Stan Uryasev. Value-at-Risk vs. Conditional Value-at-Risk in Risk Management and Optimization. In Zhi-Long Chen, S. Raghavan, Paul Gray, and Harvey J. Greenberg, editors, *State-of-the-Art Decision-Making Tools in the Information-Intensive Age*, pages 270–294. INFORMS, September 2008.

[10] Edward Anderson, Huifu Xu, and Dali Zhang. Varying confidence levels for CVaR risk measures and minimax limits. *Mathematical Programming*, 180(1-2):327–370, March 2020.

[11] D.H. Wolpert and W.G. Macready. No free lunch theorems for optimization. *IEEE Transactions on Evolutionary Computation*, 1(1):67–82, April 1997.

[12] Fernando Lezama, João Soares, Zita Vale, Jose Rueda, Sergio Rivera, and István Elrich. 2017 IEEE competition on modern heuristic optimizers for smart grid operation: Testbeds and results. *Swarm and Evolutionary Computation*, 44:420–427, February 2019.

[13] José Almeida, Joao Soares, Fernando Lezama, Zita Vale, and Bruno Francois. Comparison of evolutionary algorithms for solving risk-based energy resource management considering conditional value-at-risk analysis. *Mathematics and Computers in Simulation*, July 2023.

[14] Fernando Lezama, Joao Soares, Ricardo Faia, Tiago Pinto, and Zita Vale. A New Hybrid-Adaptive Differential Evolution for a Smart Grid Application Under Uncertainty. In *2018 IEEE Congress on Evolutionary Computation (CEC)*, pages 1–8, Rio de Janeiro, July 2018. IEEE.

[15] S. S. Shapiro, M. B. Wilk, and Mrs. H. J. Chen. A comparative study of various tests for normality. *Journal of the American Statistical Association*, 63(324):1343–1372, 1968.

[16] Jean Dickinson Gibbons and Subhabrata Chakraborti. *Nonparametric statistical inference*. Number v. 168 in Statistics, textbooks and monographs. Marcel Dekker, New York, 4th ed., rev. and expanded edition, 2003.

[17] R F Woolson. Wilcoxon Signed-Rank test. *Wiley Encyclopedia of Clinical Trials*, 2007.

[18] Ansel Y. Rodríguez-González, Ramón Aranda, Miguel Á. Álvarez Carmona, Yoan Martínez-López, and Julio Madera-Quintana. Applying ring cellular encode-decode UMDA to risk-based energy scheduling. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, pages 1–2, Boston Massachusetts, July 2022. ACM.

[19] András Vargha and Harold D Delaney. The kruskal-wallis test and stochastic homogeneity. *Journal of Educational and behavioral Statistics*, 23(2):170–192, 1998.

[20] Ansel Y Rodríguez-González, Fernando Lezama, Yoan Martínez-López, Julio Madera, Joao Soares, and Zita Vale. Wcci/gecco 2020 competition on evolutionary computation in the energy domain: An overview from the winner perspective. *Applied Soft Computing*, 125:109162, 2022.