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Metaheuristic Optimization Algorithms Comparison Adopted for the Profit Maximization of Electricity Market Participants

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Abstract: - The electricity market faces numerous challenges due to the growing demand for energy, increasing penetration of renewable energy sources, and the need for grid reliability and efficiency. To address these challenges, optimization algorithms have emerged as essential tools for optimizing various aspects of the electricity market, including generation, transmission, distribution, and demand-side management. The review can be done by providing an overview of the key components and challenges of the electricity market, including generation dispatch, unit commitment, economic dispatch, transmission network optimization, and demand response management. It then systematically examines a wide range of optimization techniques employed in addressing these challenges, including linear programming, mixed-integer linear programming, nonlinear programming, dynamic programming, genetic algorithms, particle swarm optimization, simulated annealing, and machine learning-based approaches. This paper presents a comparison of optimization algorithms, RCEDUMDA (Ring-Cellular Encode-Decode Univariate Marginal Distribution Algorithm) and CL_HC2RCEDUMDA (Hill Climbing to Ring Cellular Encode-Decode Univariate Marginal Distribution Algorithm) for the profit maximization of Electricity Market consumers & prosumers.

Keywords: Electricity market, Energy Resource Management, Metaheuristic optimization Algorithm, Smart Grid, Aggregator, Profit maximization.

I. INTRODUCTION

Smart grid technologies offer the potential for widespread adoption of distributed renewable energy sources, presenting numerous challenges for utilities and operators [1]. Within this framework, local energy markets (LEMs) facilitate energy trading among small-scale sectors at the community level, contributing to reduced environmental impact [2]. LEMs empower end-users, encouraging their involvement in energy communities and the adoption of fully transactive energy systems [3]. Previously, individuals with limited energy production capabilities faced barriers to participation in electricity markets due to regulatory constraints [4]. LEMs address this issue by providing a platform for prosumers, consumers, and producers to actively engage in energy trading [5]. The energy dealings in LEMs can be termed as a bi-level optimization problem, with all participants want to maximize their profits by refining their bidding strategies [6].

The optimization challenge within local electricity markets presents a multifaceted problem that can be approached and resolved through various perspectives and methodologies. One common formulation involves framing the participation of stakeholders in LEMs as a bi-level optimization problem [6]. Despite diverse assumptions, adaptations, and hybrid algorithmic approaches, attaining optimal or near-optimal solutions remains a significant hurdle within this domain.

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As a result, creating a reliable optimization technique that may yield nearly ideal solutions to this challenging problem is crucial. In order to solve a challenging bi-level bidding optimization problem in the context of LEMs, this work compares two metaheuristic optimization algorithms, RCEDUMDA (Ring-Cellular Encode-Decode Univariate Marginal Distribution Algorithm) [7] and CL_HC2RCEDUMDA (Hill Climbing to Ring Cellular Encode-Decode Univariate Marginal Distribution Algorithm) [8]. The following are this work's primary contributions:

- A proficient computational intelligence approach is proposed to address the inherently nonlinear and intricate bidding optimization problem within LEMs [9].

- The problem is conceptualized as a multi-period bi-level optimization challenge, wherein competitive agents at the upper-level aim to maximize their profits (referred to as a multileader problem) [10]. The bids or offers made by these agents influence the market clearing price determined at the lower-level problem (a single-follower problem), establishing a significant interdependence among their decisions [6].

- This paper provides a comparison of the leading optimization algorithms, RCEDUMDA (Ring-Cellular Encode-Decode Univariate Marginal Distribution Algorithm) and CL_HC2RCEDUMDA (Hill Climbing to Ring Cellular Encode-Decode Univariate Marginal Distribution Algorithm). The mentioned algorithms have been tested on the testbed available for the joint competition of GECCO & IEEE WCCI 2022 [11]. Notably, these algorithms demonstrated superior performance in solving the testbed "bi-level optimization of end-users' bidding strategies in local energy markets" during the international competition "Evolutionary Computation in Uncertain Environments: A Smart Grid Application," held at both the Genetic and Evolutionary Computation Conference (GECCO 2022) and the IEEE World Congress on Computational Intelligence (WCCI 2022).

- Furthermore, the efficacy of the proposed algorithm was evaluated through a case study involving a power system distribution network integrated with renewable energy sources. A comparative analysis was conducted, showcasing that RCEDUMDA consistently generates higher profits for all agents when compared to various algorithms.

This is how the remaining content is arranged. Following the introduction in Section 1 and in Section 2, methodology of algorithm of RCEDUMDA is mentioned. Section 3 shows the test system which have been adopted in real world scenario to compare the mentioned algorithms. In Section 4, the comparative results are tabled, which are obtained by running both the algorithms on a real-world case study involving a distribution system. Section 5 concludes by summarizing the key findings and recommendations for further study.

II. METHODOLOGY

In this section, the mathematical model for the measurement of risk taking into account the CVaR mechanism, is presented. Fig.1 [12] shows the proposed problem methodology of ERM. The model has the inputs like total generation data, Load Demand data, EVs data, Energy Storage Systems (ESS) data and Local Electricity Market data. The some of the input data are chosen as the extreme events for the consideration of risk-based management. With the use of VaR (Value at risk) and CVaR (Conditional value at Risk) methodology the aggregator can be protected.

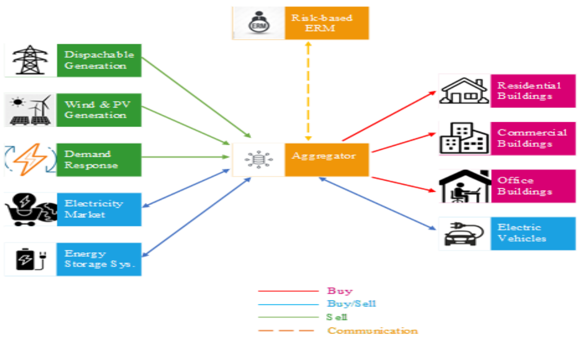

Fig.1. Energy Resourse Management [ERM] [12]

With the help of some case studies based on real scenarios the impacts of VaR and CVaR can be evaluated. Fig. 2 [11] the solution vector representation of the mentioned problem. In that the participants with the quantities are mentioned. Fig. 3 [11] shows the fitness function evaluation flowchart, according to which the mentioned ERM problem has been optimized.

The function is first called with the database containing the developed scenarios as an argument, and the value of the variable controlling risk aversion is also initialized. Each scenario is then assessed using the formulas found in the appendix section. The purpose of this review is to determine each scenario's cost, which is then saved in order to determine the estimated cost. Using the formula in [13], the $VaR\alpha$ and $CVaR\alpha$ values are determined by taking into account the projected cost, the cost of each scenario, and the probability of each scenario.

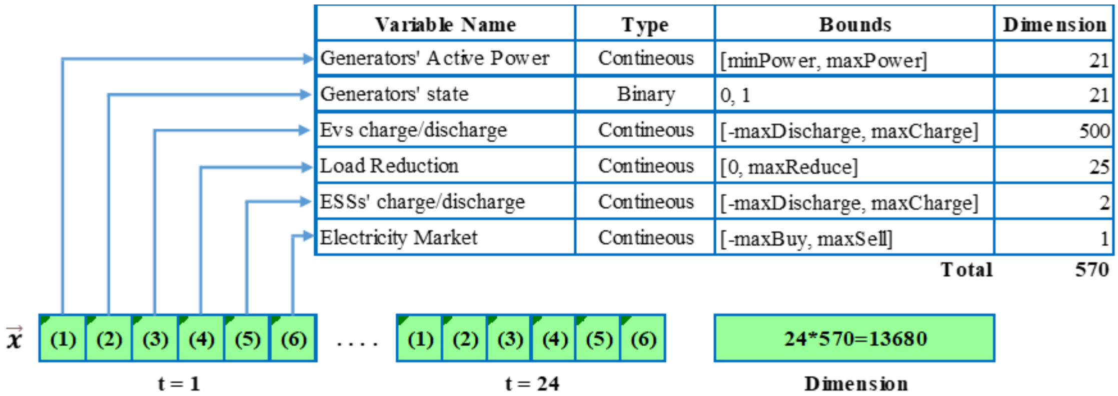

Fig. 2. Solution Vector of ERM

The aggregator makes a judgment based on the risk aversion factor after the risk-measuring parameters have been computed. Stated otherwise, the aggregator selects the optimal approach based on the OF's value.

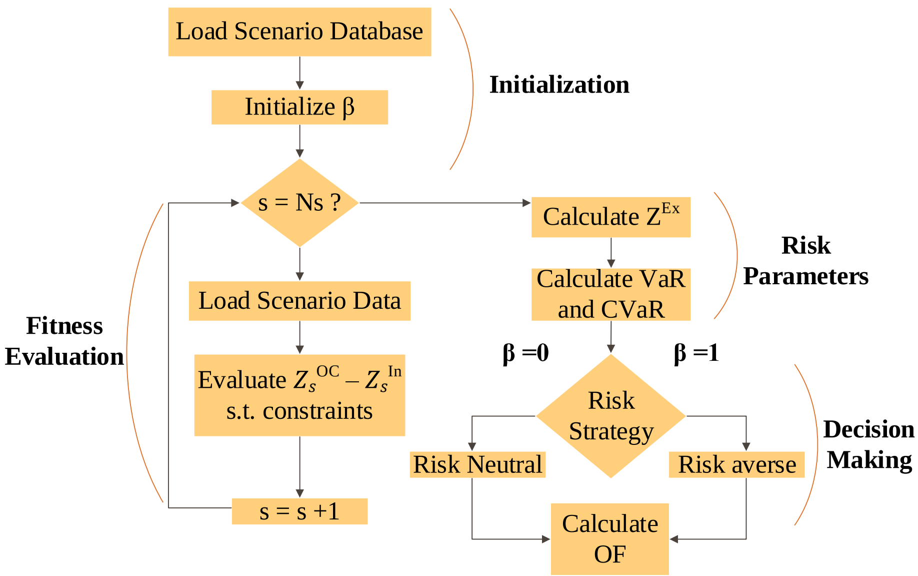

Fig. 1 Fitness Function Evaluation

When β=0, the metaheuristic just minimizes the expected cost because it does this evaluation in an effort to minimize the value of the OF in a specific number of repetitions. Nevertheless, the metaheuristic attempts to minimize both the predicted cost and the $CVaR\alpha$ for the β=1 [14].

A risk-averse plan of action for the upcoming day ERM takes into account the unpredictable behaviour of an aggregator's technology, including market prices, renewable energy generation, load consumption, and EV use patterns. In this instance, the method utilized takes into account the stochastic behaviour of these factors by running through a number of scenarios with corresponding probabilities of occurrence. The expected scenario is used to determine this aggregator's scheduling when risk is ignored. If a risk aversion strategy is not implemented, the expected cost determines the cost and value of the objective function. This can be formulated as follows: [11]

$Z_s^{tot} = Z_s^{OC} - Z_s^{In} + P_s$ (1)

$Z^{Ex} = \sum_{s=1}^{N_s} (\rho_s * z_s^{tot})$ (2)

Where, Z_s^{tot} = Total value of Objective Function

(OF) for each scenario

Z_s^{OC} = Cost of Operation

Z_s^{In} = Every scenario income

ρ_s = Respective scenario probability

Z^{Ex} = OF expected cost

P_s = Limit violation penalty

A risk-aversion strategy takes into account the risk arising from the unpredictability of the aforementioned technologies. In $(1-\rho)$% of the scenarios with the highest prices, $CVaR_\alpha$ is an extra cost applied to Z^{Ex}. The following formula [13.8] is used to compute the $CVaR_\alpha$ after determining the value of VaR_α [13]

$CVaR_\alpha(Z_s^{tot}) = VaR_\alpha(Z_s^{tot}) + \frac{1}{1-\alpha} \sum_{s=1}^{N_s} (\rho_s * \emptyset)$ (3)

Where, $\phi = \{z_s^{tot} - z^{Ex} - VaR_\alpha(z_s^{tot}) \quad if, z_s^{tot} \geq z^{Ex} + v_a R_\alpha\ (z_s^{tot})$

Otherwise, $\phi = 0$ (4)

$VaR_\alpha\ (Z_s^{tot})$ = z – score(α) * std(Z_s^{tot})

The Objective Function can be given by,

OF = $Z^{Ex} + \beta * CVaR_\alpha\,(Z_s^{tot})$ (5)

The β parameter in this case denotes the proportion of risk aversion. This option has a range of 0 to 1. The OF value is only equal to the expected cost when β=0, indicating a risk-neutral approach. Conversely, β=1 indicates that the approach has a 100% risk aversion, making it the safest option in the worst-case situations [11].

Ring-Cellular Encode-Decode Univariate Marginal Distribution Algorithm (RCEDUMDA) [7]

Input:

c = number of cells,

m = size of the cells,

$maxIt$ = maximum iteration,

l = number of elitist individuals,

s = number of selected individuals,

r = neighbourhood ratio,

α = additional occurrence,

k = number of codes,

$minB$ = vector of min bounds,

$maxB$ = vector of max bounds

Output: Best Solution

$t \leftarrow 1$

$Pop \leftarrow Create$ Ring cellular structure of c cells of size$m$

foreach cell do

Pop ($cell$) $\leftarrow m$ individuals generated randomly in [$minB$, $maxB$]

while $t \leq maxIt$ do

Select globally l elitist individuals

foreach cell do

M ←the$m$ best individuals in $neighborhood$ ($cell$, r)

eM ←$encode$ (M, k,$minB$,$maxB$)

Estimate the distribution

$p(x) = \prod_{i=1}^{l} p(x_i)$ from eM

p (x) ←$scale$ (p (x), α)

eC ←c new individuals generating according to p (x)

C ←$decode$ (eC, k, $minB$, $maxB$)

Insert C in the same cell of an auxiliary population $auxPop$

Replace the Pop with $auxPop$

Include the elitist individuals, replacing the individuals in their positions

$t \leftarrow t + 1$

$bestSolution$ ← the best individual in Pop

Given a continuous variable with the domain [$minB$, $maxB$], a number of codes k, and a value $v \in$ [$minB$, $maxB$]. The domain is divided into k uniform intervals via the encoding method, which yields the encode value ev as the interval index. The decoding method takes a value from ev and returns $minB$ for the minimum ev, $maxB$ for the maximum ev, and the middle value of the interval with index ev for the remaining situations. Third, using the best people (encoded individuals) in the neighbourhoods, RCEDUMDA estimates the univariate marginal distribution $p(x) = \prod_{i=1}^{l} p(x_i)$ scales each $P(x_i)$, and uses probability sampling to create new individuals (encoded individuals) based on this distribution. The scaling approach involves increasing the number of times each x_i in the α value. Hence, none of $P(x_i)$ is 0.

III. TEST SYSTEM

In the BISITE laboratory in Salamanca, Spain, a smart city's medium voltage distribution network was used for this case study [15]. A 30MVA substation, 15 DG units (13 PV plants and 2 wind farms) and four 1Mvar capacitor banks are all located in bus 1. There are twenty-five different loads on this network, ranging in consumption from office and residential buildings to a few service buildings like a hospital, Railway station, and shopping centre etc.

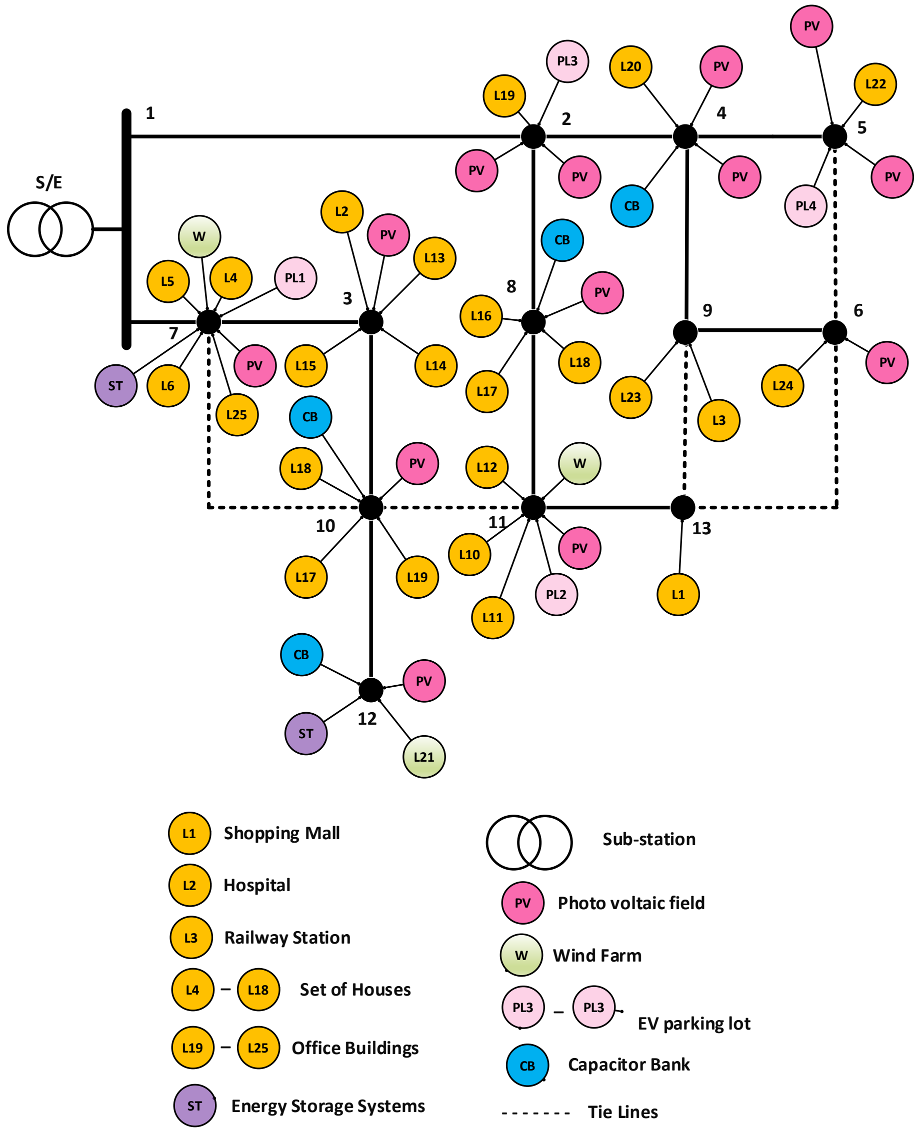

Fig.4. 13-Bus network system [11]

Table 1. Energy Sources Specifications

Energy Resource	Prices (m.u./MWh) min-max	Capacity (MW) min-max	Forecast (MW) min-max	Units
PV	29-29	--	0-0.81	13
Wind	31-31	--	0.3-3.07	2
External supplier	50-90	0-30	--	1
Storage (charge)	110-110	0-1.25	--	2
Storage (Discharge)	90-90	0-1.25	--	--
EV (charge)	0-0	0.01-0.05	--	500
EV (Discharge)	90-90	0.01-0.05	--	--
Demand Response	100-100	0-1.21	--	25
Load	0-0	--	0.01-2.38	25
Electricity Market buy & sell	29.85-104.61	--	--	1

There are three 50kW fast charging stations and four 7.2kW slow charging stations available for EV charging. The 13-bus distribution network's line diagram is shown in Fig. 4. Table 1 displays the energy resource specifications.

IV. RESULT ANALYSIS

This section compares the outcomes produced by the suggested algorithm RCEDUMDA [9] with the results produced by the competition organizers [11] using CL_HC2RCEDUMDA. Tables 2 and 3 display the CL_HC2RCEDUMDA benchmark results and benchmark situations, respectively.

Table 2. Benchmark Results of CL_HC2RCEDUMDA

Row	OF	Fex	VaR	CVaR
Run 1	15594.48	9358.87	3951.62	6235.61
Run 2	15679.27	9417.15	3958.81	6262.12
Run 3	15620.10	9467.70	3930.12	6152.39
Run 4	15544.04	9340.95	3946.99	6203.09
Run 5	16119.97	9196.15	4304.24	6923.82
Run 6	16054.55	9050.63	4124.40	7003.92
Run 7	15561.21	9398.95	3925.43	6162.26
Run 8	15562.64	9342.68	3942.34	6219.96
Run 9	16028.56	9114.93	4193.06	6913.63
Run 10	16176.06	9251.38	4206.05	6924.68
Run 11	16011.63	9085.83	4179.54	6925.80
Run 12	15534.86	9377.01	3923.87	6157.85
Run 13	15688.62	9425.84	3958.47	6262.79
Run 14	15633.79	9471.28	3925.49	6162.51
Run 15	15473.71	9340.90	3769.25	6132.81
Run 16	16177.47	9274.92	4109.01	6902.54
Run 17	16141.36	9178.41	4195.86	6962.95
Run 18	16869.67	9155.59	4535.79	7714.08
Run 19	16214.80	9292.96	4205.60	6921.83
Run 20	15476.93	9305.18	3671.44	6171.75

Table 3. Benchmark Scenarios of CL_HC2RCEDUMDA

Row	Avg Scenario	Min Scenario	Max Scenario	Std Scenario
Run 1	9909.63	8640.23	16630.45	2402.42
Run 2	9969.01	8680.72	16696.65	2406.78
Run 3	10015.29	8744.26	16720.93	2389.34
Run 4	9891.67	8615.33	16596.93	2399.60
Run 5	9781.41	8438.22	17429.75	2616.79
Run 6	9566.43	8360.80	17326.87	2507.46
Run 7	9944.63	8678.28	16675.74	2386.49
Run 8	9892.25	8608.44	16599.90	2396.77
Run 9	9666.69	8385.79	17375.70	2549.20
Run 10	9806.53	8513.47	17530.75	2557.10
Run 11	9634.19	8363.33	17330.28	2540.98
Run 12	9922.50	8649.63	16638.11	2385.55
Run 13	9977.46	8691.73	16705.27	2406.58
Run 14	10016.97	8750.70	16735.88	2386.53
Run 15	9848.91	8651.47	16628.89	2291.54
Run 16	9791.78	8567.55	17570.10	2498.10
Run 17	9728.79	8455.57	17444.82	2550.90
Run 18	9714.73	8400.78	18458.82	2757.57
Run 19	9848.10	8556.21	17572.91	2556.83
Run 20	9777.90	8638.34	16609.87	2232.08

The objective function, expected cost (Fex), value at risk, and conditional value at risk outcomes are provided by the benchmark results. The results of the benchmark scenario are assessed for the standard, minimum, maximum, and average scenario values. For the comparative analysis, the identical outcomes for RCEDUMDA will be acquired.

Table 4. Benchmark Results of RCEDUMDA

Row	OF	Fex	VaR	CVaR
Run 1	15285.20	9140.29	3920.45	6144.91
Run 2	15261.15	9114.30	3918.20	6146.85
Run 3	15303.05	9132.29	3926.66	6170.76
Run 4	15280.19	9132.17	3918.69	6148.02
Run 5	15252.22	9090.09	3924.81	6162.13
Run 6	15248.19	9104.20	3919.93	6143.99
Run 7	15263.43	9098.02	3925.36	6165.41
Run 8	15281.71	9055.85	3943.12	6225.85
Run 9	15287.04	9106.23	3929.83	6180.80
Run 10	15014.89	9325.96	3645.25	5688.93

Table 5. Benchmark Scenarios of RCEDUMDA

Row	Avg Scenario	Min Scenario	Max Scenario	Std Scenario
Run 1	9685.79	8424.81	16396.27	2383.47
Run 2	9659.32	8387.90	16375.47	2382.09
Run 3	9679.15	8406.77	16389.05	2387.24
Run 4	9677.33	8405.51	16392.99	2382.40
Run 5	9636.05	8367.07	16354.44	2386.11
Run 6	9649.60	8387.83	16360.23	2383.15
Run 7	9644.08	8374.57	16362.27	2386.45
Run 8	9605.42	8322.33	16313.62	2397.25
Run 9	9653.21	8378.92	16367.92	2389.17
Run 10	9844.80	8625.88	15619.05	2216.16

Run 11	15289.83	9124.93	3925.55	6164.90
Run 12	15287.60	9121.69	3927.43	6165.91
Run 13	15240.84	9085.82	3920.33	6155.02
Run 14	15297.15	9127.82	3928.42	6169.33
Run 15	15333.32	9127.08	3936.18	6206.24
Run 16	15304.53	9101.88	3938.39	6202.65
Run 17	15268.24	9092.39	3929.00	6175.86
Run 18	15246.33	9101.90	3917.42	6144.43
Run 19	15312.51	9123.38	3934.39	6189.13
Run 20	15249.59	9103.22	3918.32	6146.38

Run 11	9671.07	8401.44	16388.46	2386.56
Run 12	9668.36	8394.45	16383.36	2387.71
Run 13	9631.17	8359.93	16348.39	2383.39
Run 14	9674.83	8412.03	16382.83	2388.31
Run 15	9675.41	8396.91	16381.17	2393.03
Run 16	9650.91	8379.59	16353.38	2394.37
Run 17	9639.11	8366.80	16357.05	2388.66
Run 18	9646.54	8381.59	16359.75	2381.62
Run 19	9670.86	8398.36	16398.60	2391.94
Run 20	9648.32	8376.39	16363.62	2382.17

Table 4 & 5 shows the results of benchmark and scenario for RCEDUMDA respectively. The ranking index, standard deviation (PstdOF), minimum deviation (PminOF), maximum deviation (PmaxOF), variance (PvarOF) and average time are compared for both the algorithms is shown in table 6.

Table 5. Benchmark Summary

	CL_HC2RCEDUMDA	RCEDUMDA
Ranking Index	15858.18	15265.35
Pstd OF	362.91	63.95
Pmin OF	15473.71	15014.89
Pmax OF	16869.67	15333.32
Pvar OF	131705.45	4089.32
Avg Time	383.71	499.87

A lower ranking index and higher value of cost saving reflects that RCEDUMDA gives better results than CL_HC2RCEDUMDA. The time taken for the iteration is the only positive side of CL_HC2RCEDUMDA as compared to RCEDUMDA.

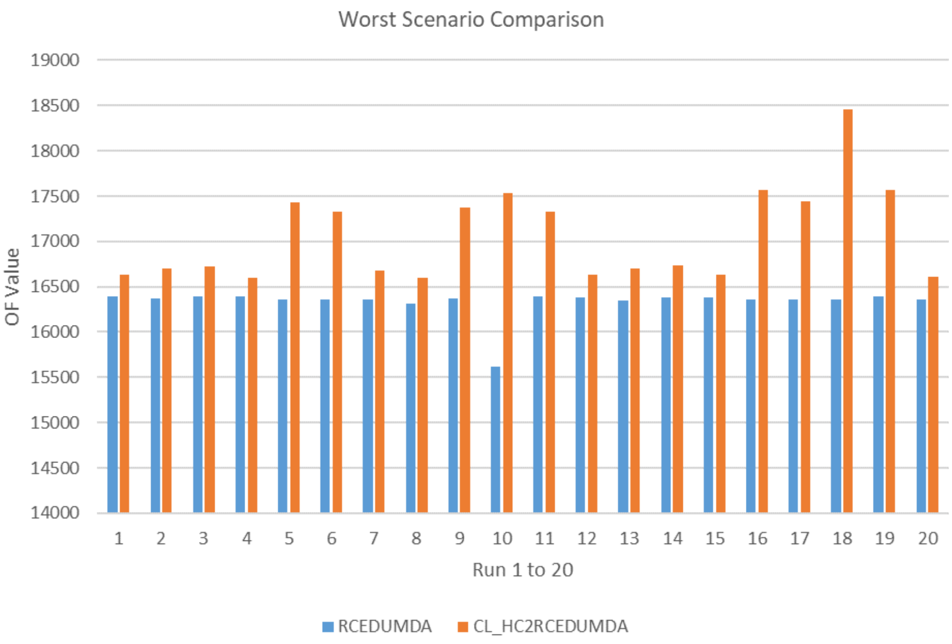

Fig.5. Worst Case Scenario Comparison

Fig. 5 shows the comparison of the worst-case scenario among the algorithms RCEDUMDA and CL_HC2RCEDUMDA. The shorter bars indicate the worthiness of RCEDUMDA over CL_HC2RCEDUMDA algorithm.

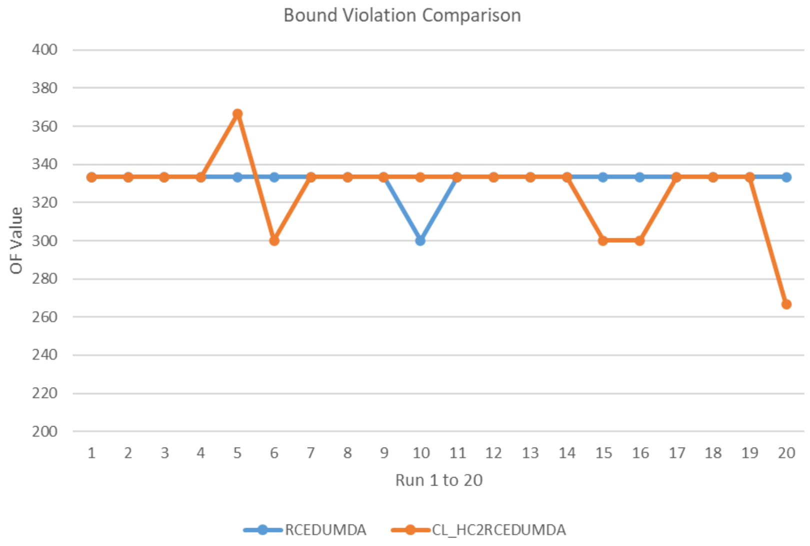

Fig.6. Bound Violations Comparison

Similarly, fig.6 & 7 shows the comparisons of bound violation and run time respectively. In case of time taken to solve the iterations CL_HC2RCEDUMDA is better but RCEDUMDA take more time to solve them efficiently with better results.

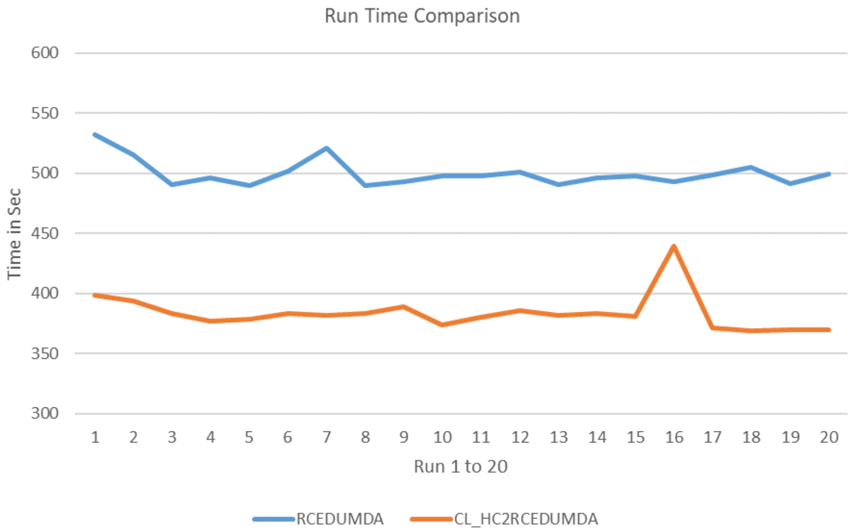

Fig.7. Run Time Comparison

As compared to the algorithm CL_HC2RCEDUMDA, RCEDUMDA algorithm demonstrated far better cost saving and profit maximization for aggregators, ranking index is lower and even in worst case scenario RCEDUMDA performed better. The future scope for this article can include the consideration of wind energy for the optimal planning of the micro grid [16], energy resources size optimization [17], smart metering [18] and EVs (Electrical Vehicles) [19] by using RCEDUMDA algorithm.

V. CONCLUSION

Energy resource management for microgrid applications has been the main emphasis of this article. The challenge of optimizing renewable power generation under harsh conditions is recognized. The outcomes were attained in compliance with GECCO & IEEE WCCI 2022 guidelines and specifications. CL_HC2RCEDUMDA, an optimization technique, is compared with RCEDUMDA for the IEEE 13 bus system and was employed in the aforementioned event. Tests were conducted for OF value, ranking index, VaR, CVaR, and run time for both metaheuristic algorithms. Comparing RCEDUMDA to CL_HC2RCEDUMDA, a notable increase in grid operating resilience is seen.

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