

Metaheuristic Optimization Techniques for Aggregator Profit Maximization and System Optimization for a Modified IEEE 14-Bus System with DER Integration in Electricity Market

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ABSTRACT

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The integration of distributed energy resources (DERs) in modern power systems necessitates advanced optimization strategies to ensure both economic viability and technical reliability. This paper presents a comprehensive comparison of four metaheuristic algorithms: Rank-based Compact Evolutionary Design Using Mutual Dependency Algorithm (RCEDUMDA), Modified RCEDUMDA, Teaching-Learning-Based Optimization (TLBO), and Particle Swarm Optimization (PSO). The algorithms are implemented on a modified IEEE 14-bus system integrated with DERs including solar photovoltaic (PV), wind turbines, and energy storage systems (ESS). The primary objective is to maximize aggregator profit while minimizing system losses, voltage deviations, and optimizing DER and ESS utilization. Evaluation metrics include convergence behavior, computational efficiency, system stability, runtime, and resource utilization. Results show that Modified RCEDUMDA achieves the highest aggregator profit with enhanced stability and efficiency, making it a robust choice for smart grid optimization.

Keywords: Metaheuristic optimization, Aggregator profit, RCEDUMDA, TLBO, PSO, Distributed energy resources, IEEE 14-bus system, Energy storage system

INTRODUCTION

The global energy landscape is transitioning towards decentralized generation through the proliferation of renewable energy sources such as solar and wind. This shift brings new challenges in terms of system stability, power quality, and economic operation. Distributed Energy Resources (DERs) (e.g. Solar Photovoltaic systems[1], Wind mills, Electric vehicles[2]) and Energy Storage Systems (ESS)[3] play a pivotal role in enhancing the resilience and sustainability of power systems.[4] However, the inherent variability of renewable sources demands advanced control and optimization techniques to harness their full potential.

In this context, aggregators serve as intermediaries that manage DERs[5], enabling participation in energy markets and grid services. Optimizing the operations of aggregators is crucial to achieving economic and technical objectives[6]. Metaheuristic algorithms are well-suited for such complex, non-linear problems due to their flexibility and global search capabilities[7]. This study compares the performance of four such algorithms on a common test platform to determine their effectiveness in optimizing DER-integrated systems[8].

METHODOLOGY

Test System Setup

The IEEE 14-bus system is modified to include DERs at specific buses:

- Solar PV at Bus 3[9]
- Wind turbine at Bus 6
- Energy Storage System at Bus 14

The network is modeled using the MATPOWER toolbox in MATLAB. The simulation is carried out for RCEDUMDA[10], Modified RCEDUMDA, TLBO and PSO optimization techniques[11]. During the runs of all the techniques, real and reactive power demands[12], DER availability profiles[13], and dynamic pricing have been observed[14].

Optimization Algorithms

- **RCEDUMDA**[15]: Employs probabilistic modeling with rank-based selection and mutual dependencies to guide search processes.[16]
- **Modified RCEDUMDA**: Enhances RCEDUMDA by incorporating adaptive learning rates and elitist selection to improve convergence.
- **TLBO**: Inspired by teaching and learning dynamics, it avoids algorithm-specific parameters, making it simple yet effective[17].
- **PSO**: Mimics the social behavior of birds flocking, optimizing solutions through collaborative exploration and exploitation[18].

Objective Function

All the above-mentioned optimization techniques are run for the profit maximization of the aggregators[19] and for the system parameters optimization. For that the mathematical model[20] has been framed with the help of the following equations.[21]

The multi-objective problem is represented as:

$$\text{Maximize } J = \alpha_1 \cdot A_{\text{Profit}} - \alpha_2 \cdot \text{Sys}_{\text{Loss}} - \alpha_3 \cdot V_{\text{Dev}} \quad (1)$$

Where:

J = Objective function to maximize

$\alpha_1, \alpha_2, \alpha_3$ = System coefficient of Aggregator profit, System loss and Voltage Deviations

A_{Profit} = Aggregator's Profit

Sys_{Loss} = Total loss of the system

V_{Dev} = Total voltage deviations

Subject to:

- Power balance constraints.
- DER generation and ESS charge/discharge limits.
- Voltage and current constraints at each bus.

PROBLEM FORMULATION

The platform opted for the runs of all the mentioned methods is modified IEEE 14 bus system with the inclusion of the DERs. The parameters which we have compared in this paper have been formulated using the following equations (2), (3), (4), (5) and (6). The overall objective function that needs to be maximized is mentioned as equation (1)[22].

Aggregator Profit Maximization

$$\text{Profit} = \sum_t (P_{\text{DER},t} \cdot \lambda_t - C_{\text{op},t}) \quad (2)$$

Voltage Deviation Minimization

$$VD = \sum_{i=1}^N |V_i - V_{\text{ref}}| \quad (3)$$

System Loss Minimization

$$P_{\text{loss}} = \sum_{i=1}^N \sum_{j=1}^N G_{ij} (V_i^2 + V_j^2 - 2V_i V_j \cos(\theta_i - \theta_j)) \quad (4)$$

DER and ESS Utilization

$$\eta_{\text{DER}} = \frac{\sum_t P_{\text{DER},t}}{\sum_t P_{\text{DER,max},t}} \quad (5)$$

$$\eta_{\text{ESS}} = \frac{\sum_t |E_{\text{dis},t}|}{E_{\text{rated}}} \quad (6)$$

Where:

η = Efficiency or Utilization

P_{loss} = System Power Loss

λ_t = Electricity Price at Time t

$P_{\text{DER},t}$ = Power Generated by DER at Time t

$C_{\text{op},t}$ = Operating Cost at Time t

$E_{\text{dis},t}$ = Energy Discharged from ESS at Time t

E_{rated} = Rated Capacity of ESS

G_{ij} = Conductance between Bus i and j

V_i, V_j = Voltage Magnitudes at Buses i and j

θ_i, θ_j = Voltage Angles at Buses i and j

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RESULTS AND DISCUSSION

Performance Evaluation

All the mentioned optimizations methods are tested on a common platform of modified IEEE 14 bus system with the integration of DERs. After the successful runs of all the techniques the following data shown in Table.1 have been obtained.

Table 1. Comparison of Metaheuristic methods over different parameters

Algorithm	Aggregator Profit (\$)	Runtime (Sec)	Convergence Iterations	Voltage Deviation (pu)	System Loss (MW)	DER Utilization (%)	ESS Utilization (%)
RCEDUMDA	920.5	12.4	55	0.032	1.23	84.2	76.3
Modified RCEDUMDA	1015.2	10.1	40	0.024	1.08	89.6	83.7

TLBO	890.2	13.2	70	0.036	1.35	80.1	71.4
PSO	870.7	11.8	65	0.041	1.48	77.9	69.2

Analysis

The comparative analysis reveals that Modified RCEDUMDA demonstrates superior performance across all key metrics. Figure 1. shows the comparison of mentioned methods on the bases of the number of iterations taken for the convergence.

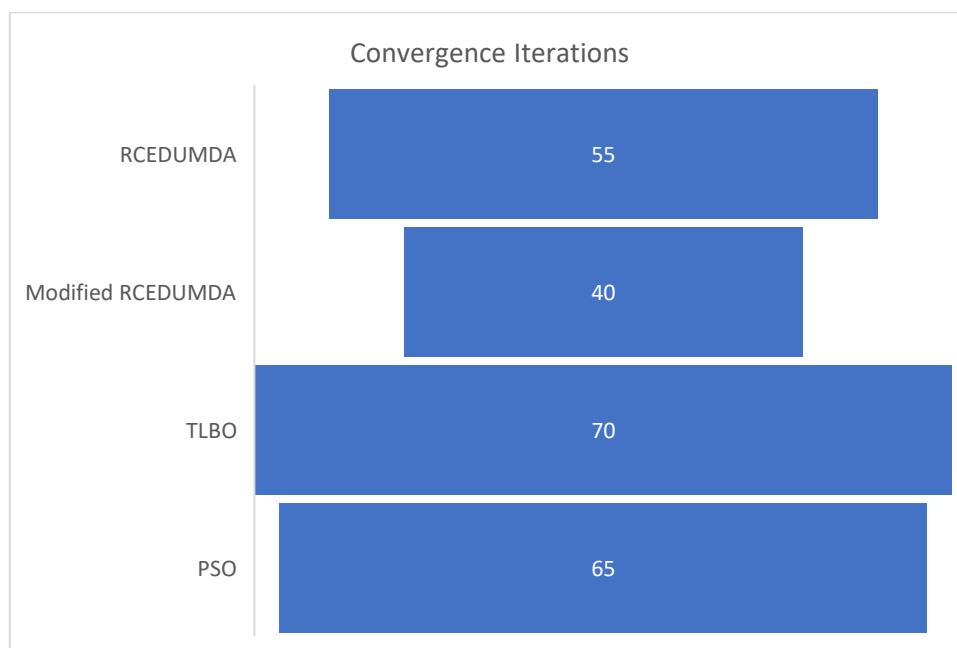


Figure 1. Nos of iterations to converge

In Figure 2. the comparison has been done for the time taken by every metaheuristic technique. In that comparison the Modified RCEDUMDA outperformed among the all.

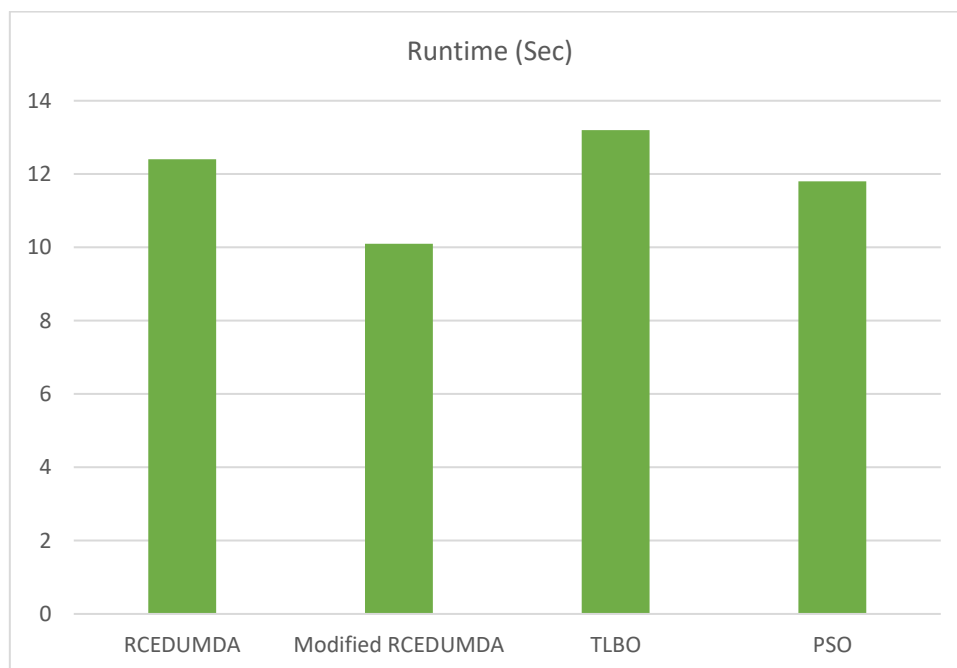


Figure 2. Runtime in seconds for every technique

Its faster convergence indicates improved exploration and exploitation mechanisms, likely due to the integration of elitist learning and adaptive parameter adjustment. This makes the algorithm particularly well-suited for systems with highly variable DER profiles. The higher aggregator profit confirms its ability to schedule DER and ESS operations effectively in response to dynamic pricing. It has been compared in the Figure 3.

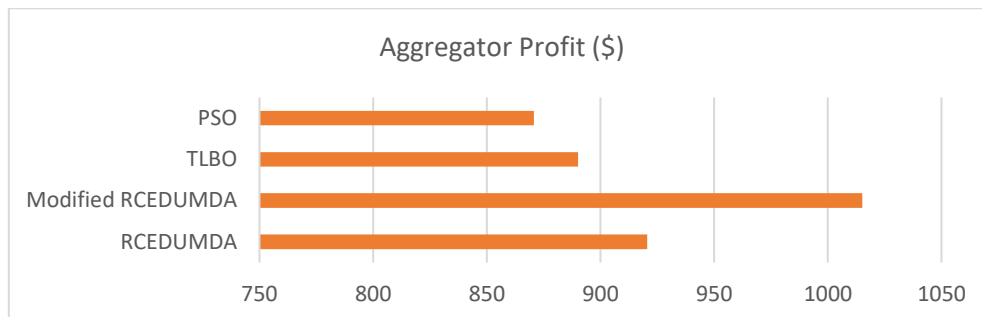


Figure 3. Aggregator profit

The system voltage deviation in pu has been plotted for all the techniques as shown in Figure 4. In that corner also Modified RCEDUMDA outperformed among the all the techniques.

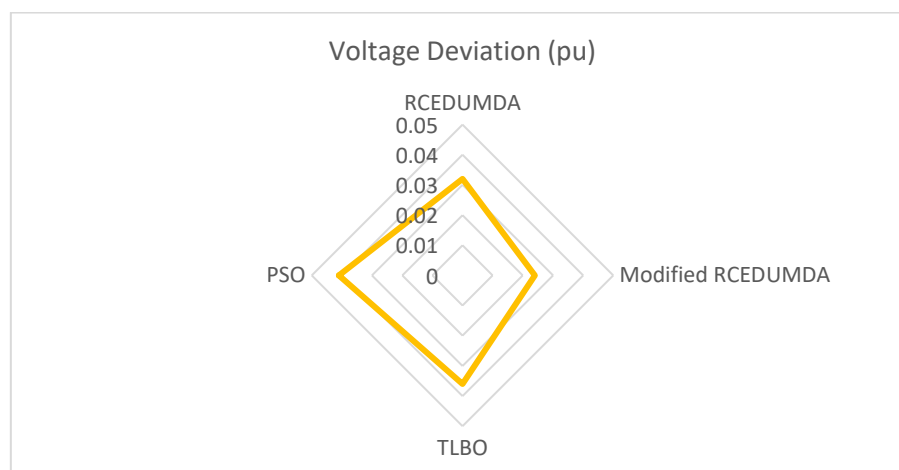


Figure 4. Voltage deviation comparison

Figure 5. show the comparison of system loss in pu. In that case also Modified RCEDUMDA outperformed among all the mentioned metaheuristic optimization techniques[23].

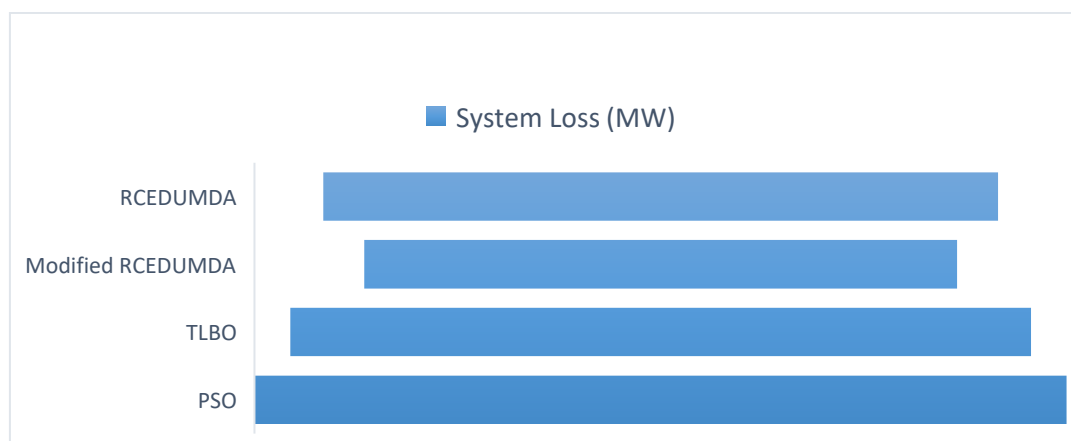


Figure 5. Total loss of the system for every technique

As shown in Figure 6, the maximum utilization of the DERs and ESS have been made by the Modified RCEDUMDA technique among the all the mentioned optimization techniques.

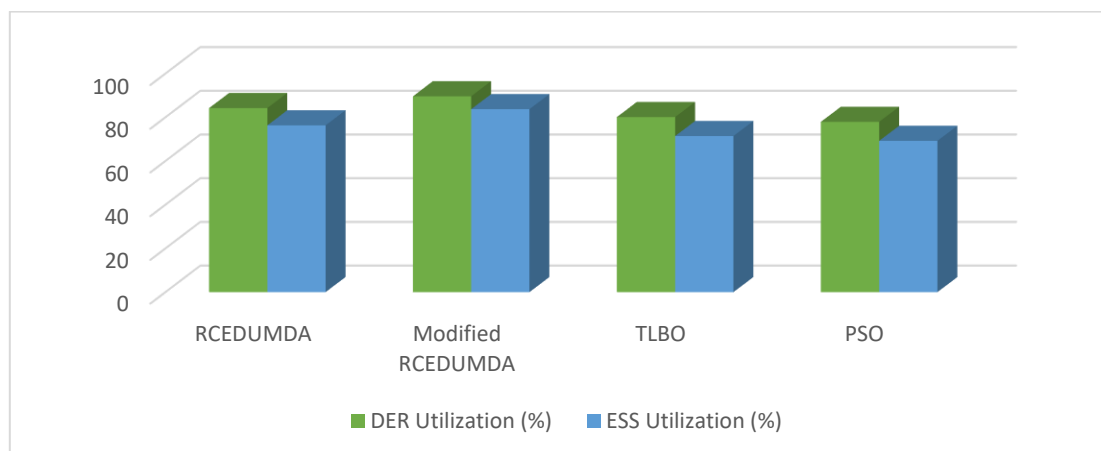


Figure 6. DERs and ESS utilization for every technique

RCEDUMDA also performed competitively, particularly in maintaining low voltage deviation and moderate losses, although it lagged behind its modified version in terms of computational efficiency. TLBO, while simple and parameter-free, showed limitations in convergence speed and optimization precision, possibly due to its less aggressive search strategy. PSO, although robust and widely applied, was outperformed in most metrics, likely because of premature convergence and sensitivity to parameter tuning.

These findings highlight the trade-offs among different optimization techniques and suggest that algorithmic customization—like the modifications in RCEDUMDA—can lead to significant improvements in performance. System operators aiming for high economic returns and grid stability should consider adopting such tailored metaheuristics.

CONCLUSION

This study underscores the effectiveness of metaheuristic algorithms in managing complex energy systems integrated with DERs. Table 2. shows the comparison of all the mentioned techniques for mentioned parameters with respect to Modified RCEDUMDA technique.

Table 2. System parameters percentage comparison w.r.t. Modified RCEDUMDA

Comparison of parameters with Modified RCEDUMDA	Optimization Technique System Parameters	As compared to TLBO	As compared to PSO	As compared to RCEDUMDA
	Aggregator Profit (\$)	14.0%	16.6%	10.3%
	Runtime (Sec)	23.5%	14.4%	18.5%
	Convergence Iterations	42.9%	38.5%	27.3%
	Voltage Deviation (pu)	33.3%	41.5%	25.0%
	System Loss (MW)	20.0%	27.0%	12.2%
	DER Utilization (%)	11.9%	15.0%	6.4%
	ESS Utilization (%)	17.2%	21.0%	9.7%

Modified RCEDUMDA performed around 14% better than TLBO, 17% better than PSO and 10% better than RCEDUMDA technique in terms of Aggregator's profit. Among the four compared techniques, Modified RCEDUMDA emerged as the most efficient in maximizing aggregator profit, enhancing system reliability, minimizing losses, lowest voltage deviations and maximum utilizations of DER & ESS. These results provide valuable guidance for system operators and researchers in selecting suitable algorithms for distributed energy optimization.

FUTURE WORK

Future extensions of this work could involve:

- Incorporating real-time demand response and electric vehicle charging dynamics
- Extending analysis to larger test systems like IEEE 33- or 69-bus networks
- Hybridizing algorithms to combine global and local optimization strengths
- Validating models using real-world DER datasets and market conditions

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