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OPTIMIZED INTEGERATION OF DISTRIBUTED ENERGY RESOURCES FOR P2P ENERGY TRADING IN DISTRIBUTION NETWORKS USING THE COS

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Abstract
The growing penetration of different types of DERs, such as PV systems, WTs, BEVs, and BESS, is gradually changing thpassive conventional distribution network into an active energy community. As the consumers become prosumers with the capability to produce, store, and trade electricity, optimal coordination of DERs is crucial for the facilitation of P2P energy trading in order to improve the local energy balance and enhance the overall performances of the distribution system. This paper presents an optimization framework to maximize the P2P trading benefits in an IEEE 12-bus radial distribution network through strategic integration and operation of DERs. The recently introduced COA is used for the optimal siting, sizing, and dispatch of PV, WT, BEVs, and BESS units with a view to maximizing the trading potential along with minimum network losses and improved voltage stability. Unlike the traditional DER scheduling models, the proposed model allows dynamic interaction between the consumers and prosumers by facilitating efficient trading of surplus renewable generation within the local network. The optimization further coordinates the charging/discharging cycles of both the BEVs and BESS units in order to improve the local energy availability and market participation of consumers in the distribution network. Comparative findings show that, in comparison to other traditional COA considerably increases the energy trading volume, lowers the active power losses, and improves the voltage profiles. The findings also demonstrate that a cost-effective and sustainable P2P energy trading environment can be established in future distribution networks through coordinated DER operation enabled by an effective metaheuristic optimizer.

Keywords: Radial Distribution Network, Peer-to-Peer, Trading, Cheetah Optimization Algorithm, Genetic Algorithm.

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1. Introduction

The growing use of distributed energy resources (DERs) namely photovoltaic (PV) panels, wind turbines (WTs), battery energy storage solutions (BESS) and battery electric vehicles (BEVs) is rapidly altering the conventional passive distribution network to an active or decentralized energy communities network [1, 2]. With the current trend of adopting renewable energy solutions and advanced storage solutions at the customer or user end, the role of electricity consumers has changed from being passive to active or prosumers who have the ability to produce, store, and trade electricity. There is, thus, a need for novel coordination mechanisms to efficiently control the DERs while ensuring network security.

In this context, peer-to-peer (P2P) energy trading was highlighted as one of the promising options for decentralized market systems that allow energy exchange between prosumers directly at the distribution level [3]. P2P energy trading helps promote energy self-consumption rates while improving the feasibility of DER investments without relying on mega grid electricity supply. According to Grid Wise Architecture Council's description, trans active energy systems rely on economic and control systems to balance energy supply and demand using "value- based" information throughout the electricity infrastructure to fulfil market objectives [4]. P2P energy trading is an example of such energy systems.

Several pilot projects and demonstration studies have been conducted to validate the feasibility of local and trans active energy markets in real-world settings, such as those found in [5]. Early research efforts initially adopted centralized optimization approaches, wherein a market operator gathers detailed operational data from all participants to determine optimal trading schedules [6]. Although central frameworks can assure optimal solutions, they increase scalability issues, data privacy, and computational burden with an increase in the number of DER-equipped prosumers.

Decentralized and distributed P2P trading mechanisms have been proposed, allowing participants to exchange the least possible information while maintaining autonomy and privacy. Auction-based and bilateral trading models also facilitate submissions of bids and offers for market clearing by prosumers with the aid of third-party coordinators. However, most of them considerably simplify or even ignore physical constraints of the power distribution network. Unlike other traditional commodity markets, the trading of electricity is subjected to network limits such as voltage bounds, line capacity limits, and power losses that need to be taken into explicit consideration to obtain feasible and secure operation [7, 8].

Recent years have seen an acceleration of P2P trading system development fuelled by advancements in information and communication technologies. The use of block chain technology has been considered for ensuring transparency and integrity of P2P trading systems for energy markets [9]. P2P trading prototypes based on bilateral contracts have been presented for P2P energy trading systems but lack constraints of distribution networks; otherwise, it would be dangerous and unrealistic for operating systems [10]. Therefore, network constraints have become an integral requirement for developing P2P energy systems.

Game theory approaches have also been explored for modelling strategic interactions in a P2P trading situation [4]. Stackelberg and hierarchical games have been employed for modelling pricing schemes and trading activities [11]. Enhancements incorporating the output limitations of renewable DERs have been proposed in [8], while [12] handled various types of DERs. Nevertheless, equilibrium solutions in various game theory-based approaches still demand certain private information related to their costs of operation, thereby undermining confidentiality. Additionally, the heterogeneity of DERs, with revenue neutrality for renewables but energy constraint for storage systems, can be improperly modelled, potentially causing unrealistic market performance.

Besides the issue of market coordination, the operational effects of P2P trading on distribution networks are also to be considered seriously. Without coordination, the effect of DER dispatch and trading may cause an increase in active losses, voltage violation, and congestion of distribution feeders, especially in an RDN. Network reconfiguration has proven to be an efficient method for mitigating problems, mainly by rearranging the network configuration by switching [13]. It has been shown in various papers that efficient reconfiguration can minimize losses, relieve congestion, and correct voltage violation problems [14, 15]. Adding more complexity by incorporating reconfiguration in P2P trading is challenging.

Because of the dynamic characteristics of renewable energy sources and BEV charging demands, optimized approaches have a pivotal role in realizing P2P energy trading between prosumers. Nevertheless, meta-heuristic-based approaches have gained popularity for handling complex, non-linear, and larger-scale optimizations with mixed variables, as well as time- variant constraints. These types of approaches possess superior global exploratory properties with non-convex solutions, rendering them more suitable for modelling DER coordination problems. Though a vast amount of research has recently been conducted, the aforementioned works on DERs are still limited, referring to few types of DERs, typically operating under static conditions. There have been fewer research attempts on integral optimization models exploring DER coordination, including P2P energy trading, specifically for RDNs.

With such research gaps, a new optimization framework for improving P2P energy trading through an optimized and integrated operation of DERs in a radial distribution network is also proposed. There is also a current interest in utilizing an optimally designed Cheetah Optimization Algorithm (COA) that optimally locates, sizes, and schedules PV panels, wind energy converters, BEVs, and BESSs in an IEEE 12-bus test network. The proposed framework takes into account optimization of constraints and an optimized operation of DERs with coordinated charging and discharging protocols. The comparisons made through various conventional optimization methods reveal that the Cheetah Optimization Algorithm optimizes and improves energy trading performances and also provides cost-effective and sustainable P2P energy trading in future networks.

2. Mathematical Modelling of the P2P Energy Trading Framework

This section mathematically expresses the proposed optimization framework for maximizing P2P energy trading in an active RDN. PV systems, WTGs, BESSs, and BEVs are all included in the model. System operational constraints such as power balance, voltage limits, and energy availability are specifically implemented to ensure safe and practical network operation.

2.1 Nodal Active Power Balance Constraint

At each bus i and time interval t, the active power balance must be satisfied as:

$$P_{i,t}^{\mathrm{PV}} + P_{i,t}^{\mathrm{WT}} + P_{i,t}^{\mathrm{BESS}} + P_{i,t}^{\mathrm{BEV}} = P_{i,t}^{\mathrm{Load}} + P_{i,t}^{\mathrm{Sell}} - P_{i,t}^{\mathrm{Buy}} \tag{1}$$

2.2 Photovoltaic Power Generation Model

The model for the PV unit's electrical output at bus *i* is as follows:

$$P_{i,t}^{\mathrm{PV}} = \eta^{\mathrm{PV}} A^{\mathrm{PV}} G_t \tag{2}$$

This formula captures the time-varying nature of solar energy production by relating PV output to solar irradiance, G_t panel area A^{PV},and conversion efficiency η^{PV}.

2.3 Wind Turbine Power Output Model

The formula for the WT power output is

$$P_{i,t}^{\mathrm{WT}} = f(v_t) \tag{3}$$

Where v_t is the wind speed at time t and $f(\cdot)$is the standard wind speed–power characteristic curve. Realistic modeling of intermittent wind generation is made possible by this formulation.

2.4 BESS Power Exchange Model

The net active power injected by the BESS is given by:

$$P_{i,t}^{\mathrm{BESS}} = P_{i,t}^{\mathrm{dis}} - P_{i,t}^{\mathrm{ch}} \tag{4}$$

2.5 BESS State of Charge Dynamics

The following factors control how the BESS state of charge (SOC) changes over time:

$$SOC_{i,t+1} = SOC_{i,t} + \eta^{\mathrm{ch}} P_{i,t}^{\mathrm{ch}} \Delta t - \frac{P_{i,t}^{\mathrm{dis}}}{\eta^{\mathrm{dis}}} \Delta t \tag{5}$$

2.6 BEV Charging and Discharging Model

The model for aggregate BEV participation in energy trading is as follows:

$$P_{i,t}^{\mathrm{BEV}} = P_{i,t}^{\mathrm{V2G}} - P_{i,t}^{\mathrm{G2V}} \tag{6}$$

2.7 BEV Energy Availability Constraint

The BEV SOC is limited by:

$$SOC_{\mathrm{min}} \leq SOC_{i,t}^{\mathrm{BEV}} \leq SOC_{\mathrm{max}} \tag{7}$$

2.8 P2P Market Clearing Condition

The following methods are used to balance the local P2P energy market:

$$\sum_{i=1}^{N} P_{i,t}^{\mathrm{Sell}} = \sum_{i=1}^{N} P_{i,t}^{\mathrm{Buy}} \tag{8}$$

2.9 Voltage Magnitude Constraint

Bus voltages are limited as follows to preserve grid security and power quality:

$$V_{\min} \leq V_{i,t} \leq V_{\max} \tag{9}$$

2.10 Objective Function: Maximization of P2P Energy Trading

The definition of the optimization goal is:

$$\max \;\; F = \sum_{i=1}^{N} P_{i,t}^{\text{Sell}} \tag{10}$$

This goal maximizes the locally traded renewable resources in each region, hence promoting the involvement of the prosumers in incrementing the local usage and decreasing the dependence on the primary grid.

The proposed formulation incorporates DER coordination, flexibility of BEVs, and constraints of network operations into an optimization scheme with a common objective of maximum P2P energy trading. The resulting constrained and nonlinear problem is solved using the COA algorithm to provide a scalable, secure, and economically sound trading platform for future active distribution networks.

3. Results and Discussion

The effectiveness of the proposed COA for P2P trading in the context of the IEEE 12- bus RDN, compared to the GA approach and the base case, will be examined in this section. The comparison will be made on the same modified IEEE 12-bus RDN represented in Figure 1 above. The comparison will be conducted for 24 hours, considering time-variant loads, renewable resources, and availability of BEVs for the following average periods:

Off-peak period: Hours 1–8
Mid-peak period: Hours 9–16
Peak period: Hours 17–24

The primary optimization objective is the maximization of P2P energy trading, while all operational constraints—including voltage limits, DER capacities, and storage operating limits are strictly satisfied.

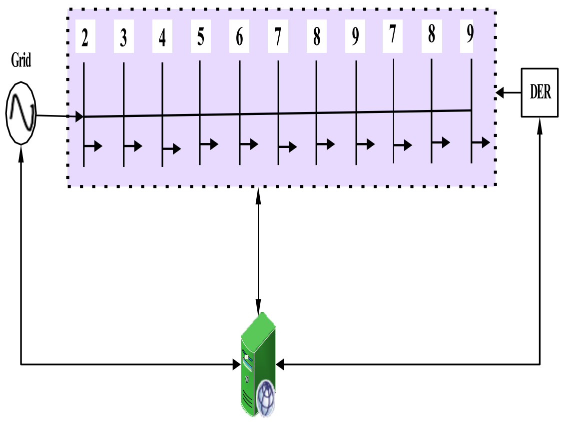

Fig 1. Modified IEEE 12-Bus RDN with Proposed work

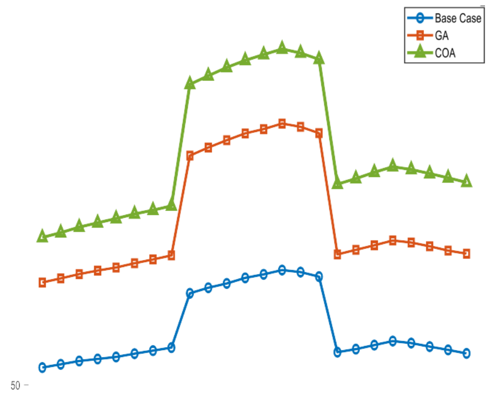

Fig 2. Hourly P2P Energy Trading Comparison

3.1 Mean P2P Energy Trading Performance

Table 1 summarizes the average P2P energy trading volumes obtained during various operational periods, and Figure 2 shows the corresponding hourly trends.

Table 1. Mean P2P Energy Trading Volume

Period	Base Case (kWh)	GA (kWh)	COA (kWh)
Off-peak	56.8	90.5	108.3
Mid-peak	86.2	140.7	168.9
Peak	62.9	101.6	129.4

As clear from Table 1 and Figure 2, it has been observed that amongst all of these methods, COA always has a maximum mean value of trading volume. Based upon the base scenario, GA brings an improvement of 50-55% in P2P trading. In a similar manner, COA brings an improvement of nearly 80-85%. Additionally, COA also maintains an improvement of 18-22% in comparison to GA, which has been observed to be more prominent at the midpoint of the peak period, especially when renewable power output has become available due to a rise in demand.

3.1 Mean DER Contribution to P2P Trading

To further understand the trading behavior, the average contribution of individual DERs in P2P trading under the COA framework is provided in Table 2, and the hourly contribution patterns are depicted in Figure 3.

Table 2. Mean DER Contribution to P2P Trading (COA Case)

Period	PV (kWh)	WT (kWh)	BESS (kWh)	BEV (kWh)
Off-peak	34	29	24	18
Mid-peak	61	42	31	25
Peak	18	36	45	34

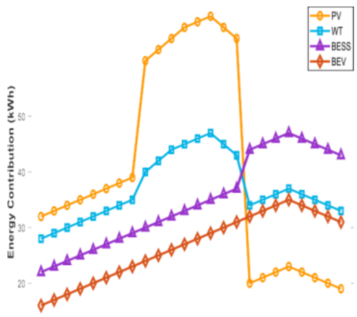

Fig 3. Hourly DER under COA

Table 3. Mean Active Power Loss

Period	Base Case (kW)	GA (kW)	COA (kW)
Off-peak	23.1	18.9	17.2
Mid-peak	28.6	22.7	20.1
Peak	32.4	26.8	23.9

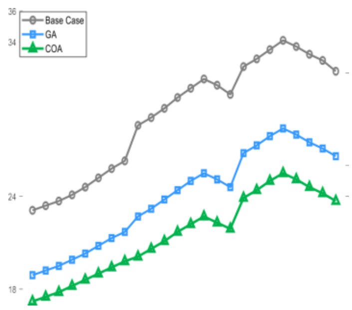

Fig 4. COA Hourly active Power Loss Comparison

3.2 Mean Active Power Loss Analysis

Although active loss minimization is not an explicitly expressed objective, C-P2P trading has an observable effect on active loss values. The total active losses for various periods of operation are represented in Table 3. Hourly active loss values are graphically represented in Figure 4.

The outcome shows that the concentration of PV exceeds that of P2P trade during MPE hours due to intermittent increases in solar irradiance. On the contrary, BESS and BEV prove to be vital during peak hours by filling the gap of lower RE generation. Greater dependence of storage- based resources during peak hours, as depicted in Figure 3, corroborates that COA performs satisfactorily while displacing energy temporally and maintaining trade despite lower RE generation.

The outcomes indicate that COA decreases the average power loss by a mean of 30% compared to the reference case and 11- 13% in comparison to GA. This margin of improvement has been mainly identified due to enhanced local interactions among consumers, thereby diminishing power transfers through distant feeders. The more even distribution loss profile pointed out in Figure 8 above has also supported the favorable side effects of P2P trading on distribution networks.

3.3 Mean Voltage Profile Performance

The mean minimum bus voltage for each operating period is used to assess voltage performance, as shown in Table 4.

Table 4. Mean Minimum Bus Voltage

Period	Base Case (p.u.)	GA (p.u.)	COA (p.u.)
Off-peak	0.964	0.974	0.979
Mid-peak	0.953	0.966	0.973
Peak	0.947	0.962	0.969

COA always sustains a relatively high and more stable voltage profile for all periods of operations, including the peak periods. The above findings thus emphasize that the maximum P2P trading will not create voltage security constraints, rather the optimized coordination of DERs has significantly improved voltage regulation and alleviated the stress on the crucial nodes in the network. The analysis of Tables 1-4 and Figures 2-4 provided above unanimously shows that the proposed COA-based approach is superior to GA and the base case in terms of maximizing P2P energy trading, along with enhancing network efficiency and voltage stability. The optimizing search and coordination trait within COA allows efficient usage of RE, ESSs, and mobile BEVs, thereby increasing local utilization of energy, lowering power losses, and ensuring operational reliability for the distribution network.

4. Conclusion

This research provided a coordinated optimization approach to maximize the extent of P2P energy trading in the IEEE 12-bus RDN using the optimal combination and management of diverse DER types like PV systems, wind energy converters, BEVs, and BESS. By performing a time-series simulation over a period of 24 hours representing the actual changes in the load demand, wind profiles, PV solar power generation, and BESS storage capacity, it was observed that the developed COA approach consistently outperformed the existing Genetic Algorithm technique and the base case without the consideration of the coordinated trading approach. The simulation outcome revealed that the COA approach increased the overall level of P2P energy trading by a maximum of 80-85% compared to the base case and by a maximum of 18-22% more than the existing algorithm without decreasing the overall active power loss in the RJHN by nearly 30% and improving the voltage magnitude profiles in all time periods. The observation of the simulation outcome satisfies the fact that a proper coordination in the generation, storage resources, and demand flexibility can enable a higher demand-side utilization without violating the safety aspects of the RJHN. Future research works should include stochastic models of the prosumers' behavioral aspects on a SJHN and at a commercial level.

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