Integrated Load and Energy Management in Active Distribution Networks Featuring Prosumers Based on PV and Energy Storage Systems

Alireza Alamolhoda, Reza Ebrahimi, Mahmoud Samiei Moghaddam, and Mahmoud Ghanbari

Abstract—**This study introduces a mixed-integer second-order conic programming (MISOCP) model for the effective management of load and energy in active distribution networks featuring prosumers. A multi-objective function is devised to concurrently minimize various costs, including prosumer electricity costs, network energy loss costs, load shedding costs, and costs associated with renewable energy resource outages. The methodology involves determining optimal active power adjustment points for photovoltaic (PV) resources and integrated energy storage systems (ESSs) within network buildings, in conjunction with a demand-side management program. To achieve the optimal solution for the proposed MISOCP model, a robust hybrid algorithm is presented, integrating the modified particle swarm optimization (MPSO) algorithm and the genetic algorithm (GA). This algorithm demonstrates a heightened capability for efficiently converging on challenging problems. The proposed model is evaluated using a distribution network comprising 33 buses, a practical distribution network, and a distribution network comprising 118 buses. Through comprehensive simulations in diverse cases, the results highlight the innovative contributions of the model. Specifically, it achieves a noteworthy reduction of 26.2% in energy losses and a 17.72% decrease in voltage deviation. Additionally, the model proves effective in augmenting prosumer electricity sales, showcasing its potential to improve the overall efficiency and sustainability of active distribution networks.**

Index Terms—**Distribution network, energy storage system, renewable energy resource, prosumer, evolutionary algorithm.**

NOMENCLATURE

A. Sets and Indexes

B, nm	Set and index of grid branches
N, n	Set and index of grid nodes
$N_{n'}$	Set of all buses that are children of node n'
S, s	Set and index of scenarios
T, t	Set and index of time

B. Parameters

σ_s	Probability of each scenario
η_{ch}, η_{dis}	Charging and discharging efficiencies of battery
ε	Amount of load changes
ρ_{ij}	The j-dimensional mutation process applied to i^{th} particle within population
B_{ij}^k	Bad position of particle i and dimension j
c_t^b, c_t^s	Cost coefficients corresponding to purchase and sale of power
c_t^p	Cost of photovoltaic (PV) power interruption
c_t^{DR}	Load shedding cost
$c_1^g(k)$, $c_2(k)$	Learning factors
$c_{1,start}^g$, $c_{1,end}^g$	Starting and ending values of training factor for global search
$c_{2,start}$, $c_{2,end}$	Starting and ending values of training factor for local search
d	Initial inertia weight after initial search
$d_{n,t}^B$	Depth of discharge (DoD) in battery
$I_{n,t}^B$	Initial percentage of energy in battery
$k_{\max}$	The maximum number of iterations
k	Number of current iterations
$\overline{P}_{n,t,s}^P$	Actual PV power in each scenario
$P_{n,t,s}^L$	Load demand
r_{nm}, x_{nm}	resistance and reactance of branch
r_1, r_2, r_3	Random numbers in the range $\{0,1\}$
ss	Search space
ΔT	Length of time slot, which is equal to 1 hour
w	Inertial weight
$w_{\max}$, $w_{\min}$	The maximum and minimum values of inertia weight coefficient

C. Variables

A_{ij}^k	Personal best value of particle i and dimension j

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D_{ij}^{k}	Global best value of particle i and dimension j
$E_{n,t}^{B}$	Remaining energy in battery
F_{ij}^{k}	Velocity of particle i and dimension j
$l_{nm,t}$	Square of branch current flow
$P_{n,t}^{b}$, $P_{n,t}^{s}$	Purchase and sale of power in building
$P_{n,t}^{P}$	Operated PV power
$P_{n,t}^{DR}$	Shifted load in demand response schedule
$P_{n,t}^{G}$	Exchange of active power between building in bus n and network
$P_{nm,t}$, $Q_{nm,t}$	Active and reactive power flows of branch
$P_{n,t}^{ch}$, $P_{n,t}^{dis}$	Charging and discharging power of battery
$v_{n,t}$	Definition of square voltage of network bus
X_{n}^{B}, $z_{n,t}^{B}$	Battery capacity and binary variable that indicates charging and discharging statuses of battery
X_{ij}^{k}	Position of particle i and dimension j

I. Introduction

THE contemporary climate and energy strategy outlined by the European Commission underscores a pivotal focus on the integration of photovoltaic (PV) systems into the power grid, aligning with the goal of achieving complete decarbonization of the European energy supply by 2050. This study proposes integrating energy storage systems (ESSs) with PV systems to manage intermittent PV production. The ESS optimizes energy management by reducing peak loads, balancing levels, and cutting electricity costs. It also creates new market opportunities for prosumers, who can manage energy consumption, generation, storage, and sales. Coordinated efforts between distribution system operators and sellers are essential. This approach aims to enhance prosumer benefits and ensure grid safety, reliability, and cost-effectiveness.

Foundational works [1]-[3] establish energy management strategies for prosumer communities. Reference [1] suggests coordinated energy management to reduce costs and improve reliability, [2] presents a smart power system for economic profit, and [3] offers a real-time framework for cooperative energy management. Later, studies [4], [5] introduce models for prosumer engagement, with [4] using a multi-agent framework for balancing premiums and [5] proposing a stochastic model for island microgrids. Further, [6] and [7] address operational constraints and optimization, with [6] focusing on medium-voltage/low-voltage (MV/LV) network integrity and [7] using particle swarm optimization (PSO) algorithms for energy management. Lastly, [8]-[10] provide optimization models to enhance network efficiency and prosumer profitability. Reference [8] uses a stochastic game for voltage regulation with PV prosumers. Reference [9] offers an optimization model to reduce network losses and boost prosumer profits. Reference [10] addresses voltage imbalances for household satisfaction. Reference [11] presents a two-stage system for balancing the network based on prosumer behavior. Reference [12] introduces a model to cut costs for thermal prosumers using thermal storage. Reference [13] proposes a two-level optimization framework for reactive power distribution. Reference [14] introduces optimal volt/var control to reduce power losses. Reference [15] presents a carbon emission model for grids with renewables and storage. Reference [16] uses a Markov model to optimize heating system reliability. Reference [17] offers a framework for dynamic PQ operational envelopes. Reference [18] uses alternating direction method of multipliers (ADMM) for robust multi-agent scheduling. Reference [19] proposes an AC-DC hybrid energy management approach with fuzzy logic. Reference [20] suggests a home-area energy management strategy for demand response. Reference [21] offers a two-stage method for congestion management in active distribution networks with various energy resources. Reference [22] introduces a real-time control system for integrated transmission and distribution networks using geographic information system (GIS). Reference [23] proposes a prosumer-based energy sharing mechanism to maximize social welfare. Reference [24] uses time-series simulations for autonomous network management. Reference [25] presents an artificial electric field algorithm (AEFA) for cost-effective PV-wind-battery systems. Reference [26] proposes a whale optimization algorithm (WOA) for economic emission dispatch in microgrids. Reference [27] introduces a distributed management approach for prosumers' energy operations with storage. Reference [28] offers an optimal dispatch approach using locational marginal prices. Reference [29] introduces an evolutionary method for optimizing distribution systems. Reference [30] presents a stochastic model for coordinating electricity and gas networks. Reference [31] introduces a probabilistic framework for managing transmission congestion. Reference [32] offers a comprehensive approach to congestion management using renewable energy sources (RESs) and ESSs. Reference [33] presents a neural network for home energy management in solar houses. Reference [34] proposes an energy management framework for coordinating electric vehicle (EV) charging with distribution systems using improved artificial cell swarm optimization and marine predator algorithm (IACSO-MPA).

Existing studies on load and energy management in active distribution networks with prosumers often lack a comprehensive model considering multi-objective functions and hybrid optimization algorithms. Most focus on individual aspects with simpler techniques. This paper fills the gap by introducing a mixed-integer second-order conic programming (MISOCP) model with multi-objective functions for addressing prosumer electricity costs, network energy loss costs, load shedding costs, and costs associated with renewable energy resource outages, using a hybrid algorithm combining modified particle swarm optimization (MPSO) and genetic algorithm (GA) to leverage their complementary strengths for multi-objective optimization. MPSO excels in exploring large solution spaces and rapid convergence, while GA is effective in handling multiple objectives and maintaining diverse solutions. This combination aims to improve performance and convergence to Pareto-optimal solutions, addressing the complexities of our optimization problem more effectively than using either algorithm alone.

This hybrid algorithm offers a more robust solution for complex challenges, as shown in Table I, highlighting its unique consideration of demand-side management, resource uncertainty, and prosumers based on PV and ESSs.

TABLE I
COMPARISON OF THIS STUDY WITH SIMILAR REFERENCES

Reference	Algorithm	Model	Grid model	Prosumer	ESS	PV	Multi-objective	Stochastic	Demand response
[1]	Sub-gradient methods	Linear	-	√	√	√	√	√	-
[2]	GA	Non-linear	-	√	-	√	-	√	-
[3]	Simplex	MILP	-	√	-	√	√	√	√
[4]	Unknown	Non-linear	√	√	-	-	√	-	-
[5]	Simplex	MILP	-	√	√	√	-	√	√
[6]	Simplex	MILP	√	√	√	√	-	-	-
[7]	PSO	Non-linear	√	√	-	√	-	-	-
[8]	Simplex	MILP	√	√	-	√	-	√	-
[9]	Simplex	SOCP	√	√	√	√	√	-	-
[10]	Heuristic	Non-linear	√	√	√	√	-	-	-
[11]	Newton's method	Non-linear	√	√	√	√	-	-	-
[12]	Newton's method	Non-linear	-	√	-	-	-	-	-
[13]	Simplex	MILP	√	√	-	-	√	√	-
[14]	Evolutionary algorithm	Non-linear	√	√	√	√	√	-	-
[15]	Unknown	Non-linear	√	√	√	√	√	-	-
[16]	Heuristic	Markov	-	√	-	-	√	-	-
[17]	Newton's method	Non-linear	√	√	√	√	-	-	-
[18]	ADMM	SOCP	√	-	√	√	√	-	-
[19]	Fuzzy	Non-linear	√	-	√	√	-	-	-
[20]	Unknown	Non-linear	√	-	√	-	√	-	√
[21]	Simplex	SOCP	√	-	√	√	√	-	√
[22]	Unknown	Non-linear	√	-	√	√	-	-	-
[23]	Simplex	MILP	-	√	√	√	-	-	√
[24]	Unknown	Linear	√	-	-	√	√	-	-
[25]	AEFA	Non-linear	√	-	√	√	√	-	-
[26]	WOA	Non-linear	√	-	√	√	√	-	√
[27]	Simplex	MILP	√	√	√	√	√	-	-
[28]	Simplex	MIQP	√	√	-	-	√	-	√
This study	MPSO-GA	MISOCP	√	√	√	√	√	√	√

Note: MILP stands for mixed-integer linear programming; SOCP stands for second-order conic programming; MIQP stands for mixed-integer quadratic programming; √ represents that the item is considered; and - represents that the item is not considered.

The contributions of this study are as follows.

1) A novel hybrid algorithm integrating MPSO and GA is introduced for better and faster problem-solving.

2) An MISOCP model is developed for the effective management of load and energy in active distribution networks, considering network objectives, prosumers based on PV and ESSs, demand-side management, and renewable energy resource uncertainty.

The remainder of this paper is structured as follows. In Section II, we present and fully explain the proposed formulation. Afterwards, in Section III, we analyze the results obtained from simulations. Finally, in Section IV, we provide our concluding remarks along with some suggestions for future research.

II. PROPOSED FORMULATION

In this section, the proposed model and algorithm are presented. Also, the uncertainty of PV resources based on the discrete scenario method is presented.

A. Proposed Optimization Model

The multi-objective function in this study optimizes the load and energy management in active distribution networks featuring prosumers, which aims to minimize the prosumer electricity costs, network energy loss costs, costs associated with PV power curtailment, and load shedding costs to improve system performance, efficiency, and sustainability.

The first objective function (1) is to reduce the cost of purchasing and selling energy for prosumers.

$$F_1\left(P_{n,t}^b, P_{n,t}^s\right) = \sum_{n \in N}\sum_{t \in T}\left(c_t^b P_{n,t}^b - c_t^s P_{n,t}^s\right)\Delta T \tag{1}$$

The second objective function (2) is to minimize the network energy loss costs.

$$F_2(B)=\sum_{nm\in B}\sum_{t\in T}c_t^b\left(r_{nm}l_{nm,t}\right)\Delta T \tag{2}$$

The third objective function (3) is to reduce the costs associated with PV power curtailment

$$F_3\left(P_{n,t}^P\right)=\sum_{s\in S}\sigma_s\left(\sum_{n\in N}\sum_{t\in T}c_t^p\left(\overline{P}_{n,t,s}^P-P_{n,t}^P\right)\Delta T\right) \tag{3}$$

The fourth objective function (4) is to reduce load shedding costs.

$$F_4\left(P_{n,t}^{DR}\right)=\sum_{s\in S}\sigma_s\left(\sum_{n\in N}\sum_{t\in T}c_t^{DR}\left(P_{n,t,s}^L-P_{n,t}^{DR}\right)\Delta T\right) \tag{4}$$

Thus, the multi-objective function of the proposed model can be expressed as (5), and the related constraints are presented in (6)-(24).

$$F_T=\min\left(F_1+F_2+F_3+F_4\right) \tag{5}$$

s.t.

$$P_{n,t}^b, P_{n,t}^s\geq 0 \quad \forall n\in N, t\in T \tag{6}$$

$$c_t^b\geq c_t^s \quad \forall t\in T \tag{7}$$

$$P_{n,t}^G=P_{n,t}^b-P_{n,t}^s \quad \forall n\in N, t\in T \tag{8}$$

$$P_{nm,t}=r_{nm}l_{nm,t}+P_{n,t}^G+\sum_{n'\in N_{n'}, n'\neq n}P_{mn',t} \quad \forall nm\in B, t\in T \tag{9}$$

$$Q_{nm,t}=x_{nm}l_{nm,t}+Q_{n,t}^{DR}+\sum_{n'\in N_{n'}, n'\neq n}Q_{mn',t} \quad \forall nm\in B, t\in T \tag{10}$$

$$v_{n,t}=v_{m,t}-2\left(r_{nm}P_{nm,t}+x_{nm}Q_{nm,t}\right)+\left(r_{nm}^2+x_{nm}^2\right)l_{nm,t} \quad \forall nm\in B, t\in T \tag{11}$$

$$l_{nm,t}v_{n,t}\geq P_{nm,t}^2+Q_{nm,t}^2 \quad \forall nm\in B, t\in T \tag{12}$$

$$\underline{v}_n\leq v_{n,t}\leq \overline{v}_n \quad \forall n\in N, t\in T \tag{13}$$

$$P_{n,t}^G=P_{n,t}^{DR}-P_{n,t}^P-P_{n,t}^{dis}+P_{n,t}^{ch} \quad \forall n\in N, t\in T \tag{14}$$

$$0\leq P_{n,t}^P\leq \overline{P}_{n,t,s}^P \quad \forall n\in N, t\in T, s\in S \tag{15}$$

$$E_{n,t+1}^B=E_{n,t}^B+\left(\eta_{ch}P_{n,t}^{ch}-1/\eta_{dis}P_{n,t}^{dis}\right)\Delta T \quad \forall n\in N, t\in T \tag{16}$$

$$0\leq P_{n,t}^{ch}\leq z_{n,t}^B X_n^B \quad \forall n\in N, t\in T, z\in\{0,1\} \tag{17}$$

$$0\leq P_{n,t}^{dis}\leq\left(1-z_{n,t}^B\right)X_n^B \quad \forall n\in N, t\in T, z\in\{0,1\} \tag{18}$$

$$X_n^B d_{n,t}^B\leq E_{n,t}^B\leq X_n^B \quad \forall n\in N, t\in T \tag{19}$$

$$E_{n,t}^B=I_{n,t}^B X_n^B \quad \forall n\in N, t=1 \tag{20}$$

$$\sum_{t\in T}P_{n,t}^{DR}\leq\sum_{t\in T}P_{n,t,s}^L \quad \forall n\in N \tag{21}$$

$$P_{n,t,s}^L-P_{n,t,s}^L\varepsilon\leq P_{n,t}^{DR}\leq P_{n,t,s}^L+P_{n,t,s}^L\varepsilon \quad \forall n\in N, t\in T, s\in S \tag{22}$$

$$\sum_{t\in T}Q_{n,t}^{DR}\leq\sum_{t\in T}Q_{n,t,s}^L \quad \forall n\in N \tag{23}$$

$$Q_{n,t,s}^L-Q_{n,t,s}^L\varepsilon\leq Q_{n,t}^{DR}\leq Q_{n,t,s}^L+Q_{n,t,s}^L\varepsilon \quad \forall n\in N, t\in T, s\in S \tag{24}$$

Constraint (6) demonstrates that the purchased or sold power is greater than or equal to zero. Constraint (7) indicates that the energy purchase cost must be greater than or equal to the energy sale cost. Constraint (8) demonstrates the balance of purchasing and selling energy between the building in bus n and the network. Constraints (9) and (10) show the balance of active and reactive power in the network, respectively. Constraint (11) displays the definition of the square voltage of the network bus. Constraint (12) relates power flow with bus voltages and line current. Constraint (13) illustrates the network bus voltage limit, where $\overline{v}_n=1.1^2$ and $\underline{v}_n=0.9^2$ are the upper and lower limits of the square of the network bus voltage, respectively. Constraint (14) shows the power balance in the building with a prosumer. Constraint (15) shows the limit of using PV power. Constraint (16) demonstrates the remaining energy in the battery. Constraints (17) and (18) display the charging and discharging power of the battery, respectively. Constraint (19) shows the limit of energy stored in the battery. Constraint (20) illustrates the initial state of energy in the battery. Constraints (21) and (22) demonstrate the changes in the real flexible load and its range in the demand response program, respectively. Similarly, constraints (23) and (24) are for changes in the reactive flexible load and its range in the demand response program, respectively.

Figure 1 shows the proposed model for load and energy management in the active distribution network featuring prosumers based on PV and ESS and flexible loads.

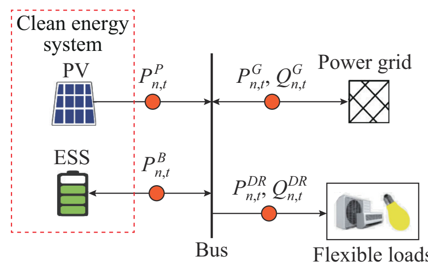

Fig. 1. Proposed model for load and energy management in active distribution network.

B. Proposed Hybrid Algorithm

This paper introduces a new hybrid algorithm combining MPSO and GA to solve the proposed model. MPSO, simulating bird hunting behavior, searches for optimal solutions by dynamically adjusting particle velocities in d-dimensional space. The MPSO identifies and avoids bad positions, enhancing convergence speed and achieving global optimal results. This is expressed by $c_1^b r_2\left(X_{ij}^k-B_{ij}^k\right)$ in the update function of the PSO. Besides, unlike the classic model of the PSO, where the weighting coefficients and training factors are considered fixed, in this paper, these coefficients are updated every time the PSO algorithm is repeated to prevent the movement of collective and individual particles toward the local optimal positions.

The weighting mechanism possesses the capability to dynamically adjust both the global and local search functionalities of the algorithm. In contrast to the conventional PSO, where the inertia weight decreases steadily, providing robust global exploration early and potent local search capabilities later, it often succumbs to premature convergence. To tackle this issue, we have devised a technique to attenuate the inertia weight factor. In the initial exploration phase, the inertia weight factor declines in a non-linear fashion, enriching the capacity of the algorithm for thorough exploration during this stage, thus facilitating an early transition to local search. Following this, after k iterations, the inertia weight factor shifts to linear decrement, ensuring the stability of the PSO algorithm in uncovering optimal solutions. Equations (25)-(27) show the standard form of the PSO algorithm. The adjustment procedure of the proposed hybrid algorithm is delineated as (28). Equation (28) means that the algorithm does not get stuck searching for local positions, but can perform a global search according to individual and collective components. The updates of inertia weight and training factor are defined by relations (28) to (32).

$$\begin{cases} F_{ij}^{k}=0 \\ X_{ij}^{k}=rand\{ss\} \end{cases} \tag{25}$$

$$F_{ij}^{k+1}=wF_{ij}^{k}+c_1^g r_1\left(A_{ij}^{k}-X_{ij}^{k}\right)+c_1^b r_2\left(X_{ij}^{k}-B_{ij}^{k}\right)+c_2 r_3\left(D_{ij}^{k}-X_{ij}^{k}\right) \tag{26}$$

$$X_{ij}^{k+1}=X_{ij}^{k}+F_{ij}^{k+1} \tag{27}$$

$$w=\begin{cases} w_{\min}+\left(w_{\max}-w_{\min}\right)l_1(k) & k<k_{\max} \\ 2w_{\min}+2\left(d-w_{\min}\right)l_2(k) & k\geq k_{\max} \end{cases} \tag{28}$$

$$l_1(k)=\mathrm{e}^{-30\left(k/k_{\max}\right)^{15}} \tag{29}$$

$$l_2(k)=-\frac{k}{k_{\max}} \tag{30}$$

$$c_1^g(k)=\left(c_{1,start}^g-c_{1,end}^g\right)\tan\left(0.875\left(1-\left(\frac{k}{k_{\max}}\right)^{0.6}\right)\right)+c_{1,end}^g \tag{31}$$

$$c_2(k)=\left(c_{2,start}-c_{2,end}\right)\arctan\left(2.8\left(1-\left(\frac{k}{k_{\max}}\right)^{0.4}\right)\right)+c_{2,end} \tag{32}$$

Equation (25) demonstrates the initial value of particle i and dimension j at iteration k. For $k=1$, the initial velocity is zero and the initial position is randomly selected from the search space. Equation (26) is the velocity update relation at iteration $k+1$. Equation (27) shows the new position of particles at iteration $k+1$. The inertial weight w is calculated from (28) and nonlinear relationships (29) and (30). The parameters $c_1^g(k)$ and $c_2(k)$ are dynamically adjusted using the tangent function (31) and (32) to establish a better balance between global and local searches. However, related studies illustrate that as the number of PSO iterations increases, the diversity of the particle population is easily lost and situated in a local optimum.

In this paper, the concept of integrating GA and MPSO is explored to solve the proposed model, aiming to enhance the population by performing crossover and mutation operations. The optimal ability of particles is useful in MPSO and causes the algorithm to leave the local optimal point. The GA encodes the problem to be solved in a chromosome and obtains the optimal solution by optimizing the operations of selection, crossover, and mutation of the chromosome.

Crossover combines genetic information from parent solutions to generate offspring. Mutation introduces random changes to maintain diversity. Thus, crossover and mutation methods, rates, and parameters should be detailed.

To overcome local optima, we propose a PSO modification inspired by GA mutation. It randomly alters one dimension of the position of each particle, expanding exploration scope and enhancing the global solution discovery [35]:

$$\rho_{ij}=5\cdot rs \quad x>0.95 \tag{33}$$

A change is triggered when a randomly generated number x falls above 0.95, with rs representing a randomly selected value between 0 and 1.

The proposed hybrid algorithm merges the randomness of GA with the strengths of MPSO for global optimization. Its flowchart is shown in Fig. 2. This algorithm is promising for the load and energy management in active distribution networks.

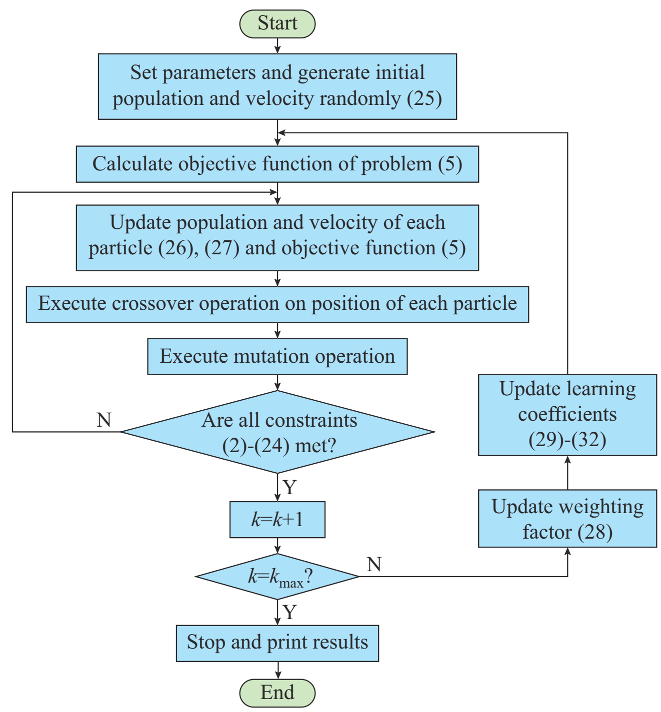

Fig. 2. Flowchart of proposed hybrid algorithm.

III. Simulation Results

A. 33-bus Test Network

In this subsection, we analyze simulation results in a 33-bus distribution network using a Julia-based algorithmic code. The simulations run on a laptop with 16 GB RAM and an Intel Core i7 CPU, ensuring efficient execution. Prosumers are strategically placed at specific locations, each comprising self-load, PV resources, and batteries. Figure 3 visually depicts the network layout and prosumer locations, aiding in understanding the simulation dynamics.

Load and PV uncertainties are addressed using a scenario-based stochastic method, with ±20% variations from baseline levels. Nodal loads have uniform probability distributions, generating 50 equiprobable scenarios. PV uncertainty is treated similarly, creating scenarios for unpredictable variations [30]. In this paper, equal probabilities (σ_s) are assigned to each scenario. For instance, if 50 scenarios are considered, then the probability associated with each scenario will be 1/50.

The parameter values are configured as follows: $c_{1,end}^{g}=0.5$, $c_{1,start}^{g}=2.5$, $c_{2,start}=1$, $c_{2,end}=3$, $w_{\min}=0.5$, $w_{\max}=1$, and $k_{\max}=100$.

The simulation results are examined and compared in several different cases, which are as follows.

Case 1: without considering the demand-side management.

Case 2: considering demand-side management with a 5% load change.

Case 3: considering demand-side management with a 10% load change.

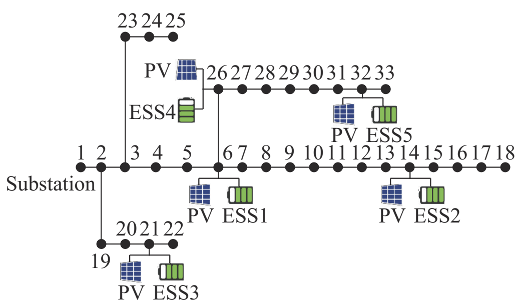

Fig. 3. Topology of 33-bus distribution network.

Table II serves as a comprehensive showcase of the outcomes derived from the various cases explored within this study. The impact of demand-side management on critical metrics, including energy losses, voltage levels, peak load, and the overall optimization objective function, is unmistakably evident. The table illuminates the notable improvements achieved in these indicators when demand-side management strategies are incorporated into the model. One noteworthy observation is the discernible enhancement in network indicators with the progressive increase in variable loads. As variable loads escalate, there is a consistent trend of improvement in both the network performance and the behavior of prosumers. A compelling example lies in the comparison of energy exchange differentials among prosumers across the cases. In Case 1, the contrast between energy purchasing and selling by prosumers amounts to 17.81 MW, a figure that diminishes to 17.05 MW in Case 3. This reduction indicates a more balanced and efficient energy utilization among prosumers, a positive outcome of demand-side management. The impact of variable loads on energy losses is also palpable. For instance, the energy loss over a 24-hour period in Case 1 stands at 194.9 kW, whereas this value decreases to 167 kW and 143 kW in Cases 2 and 3, respectively. The correlation between load variations and the reduction of energy losses underscores the effectiveness of demand-side management in mitigating energy wastage within the system. Further examination of voltage deviation reinforces the beneficial effects of demand-side management. In Case 1, the voltage deviation is 0.0632 p.u, and in Case 2, it decreases to 0.058 p.u.. The trend continues in Case 3, resulting in a further reduction to 0.052 p.u.. This indicates that demand-side management plays a pivotal role in maintaining voltage stability, which is a crucial aspect of network performance. A key achievement highlighted in the results is the absence of load shedding in any of the cases. This is attributed to the inclusion of the load shedding cost function in the optimization objective, demonstrating the efficacy of the proposed model in adeptly managing load and energy without resorting to load shedding. This finding underscores the success of the demand-side management program in achieving its intended goals in the context of load and energy management.

TABLE II
COMPARISON OF OPTIMAL 24-HOUR OPERATION RESULTS OF EACH CASE IN 33-BUS DISTRIBUTION NETWORK

Case	Energy loss (MWh)	The minimum voltage (p.u)	The maximum voltage (p.u)	Load shedding (MW)	Total electricity sale of prosumers (MW)	Total electricity purchase of prosumers (MW)	Peak load (MW)	CPU time (s)
1	0.1430	0.9800	1.032	0	19.59	2.534	0.378	8.0
2	0.1670	0.9780	1.036	0	19.95	2.530	0.398	7.5
3	0.1949	0.9768	1.040	0	20.30	2.490	0.420	5.0

Another point that can be expressed in this table is that the peak load of the network is also reduced by considering the demand-side management. As can be observed, the peak load of the network in Case 1 is equal to 420 kW, while that in Cases 2 and 3 is equal to 398 kW and 378 kW. The obtained results demonstrate the optimal performance of the proposed model and algorithm in the optimal load and energy management in active distribution networks, considering prosumers based on PV and ESSs.

Figure 4 compares the battery charging and discharging patterns of prosumers across cases, revealing strategic energy management. Prosumers charge batteries during off-peak periods and discharge batteries during peak periods for economic optimization. This strategy may vary based on individual consumption patterns. Some prosumers with excess capacity may sell stored energy during high-demand periods, but costs must be carefully considered. Overall, Fig. 4 offers insights into economic implications and strategic energy management.

Figure 5 compares the total load demands of distribution network over 24 hours, highlighting a substantial reduction in peak load with a 10% load change due to demand-side management. Figure 6 compares the average voltages of the distribution network, indicating optimal regulation in Case 3. Figure 7 illustrates the energy transactions of prosumers, with sales during high-demand periods and purchases during low-demand periods. Figures 5-7 demonstrate the positive effects of demand-side management on network performance, voltage regulation, and prosumer transactions.

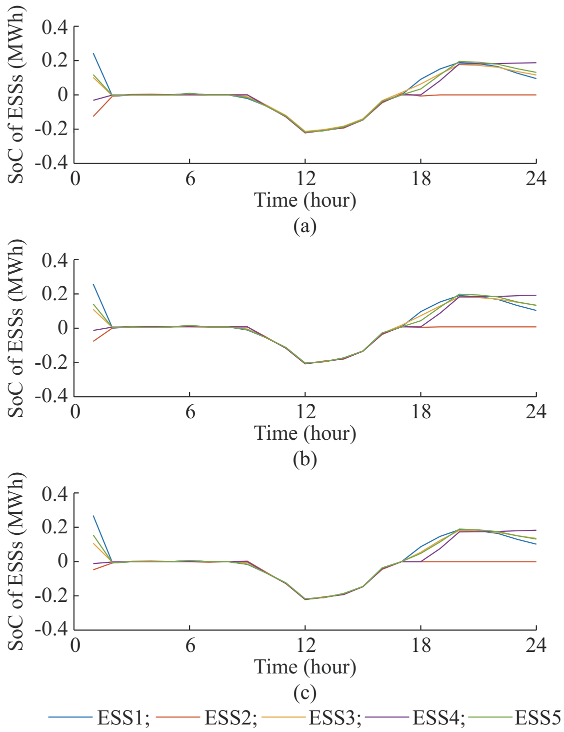

Fig. 4. Comparison of battery charging and discharging patterns of prosumers across cases. (a) Case 1. (b) Case 2. (c) Case 3.

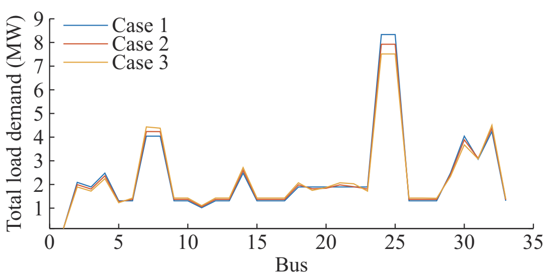

Fig. 5. Comparison of total load demands of distribution network in 24 hours per bus in each case.

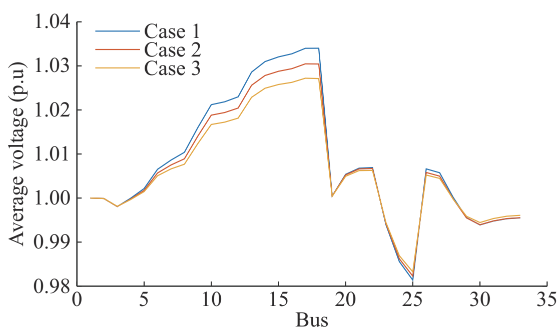

Fig. 6. Comparison of average voltages of distribution network in each case.

The simulation results offer a precise evaluation of the proposed model and algorithm, revealing the significant impact of flexible loads on energy transactions of prosumers and battery management. Flexible loads optimize energy utilization and influence network metrics such as peak loads and voltage stability. They play a vital role in achieving a balanced and efficient distribution network, highlighting the effectiveness of the proposed model in enhancing energy efficiency, cost-effectiveness, and network resilience through demand-side management.

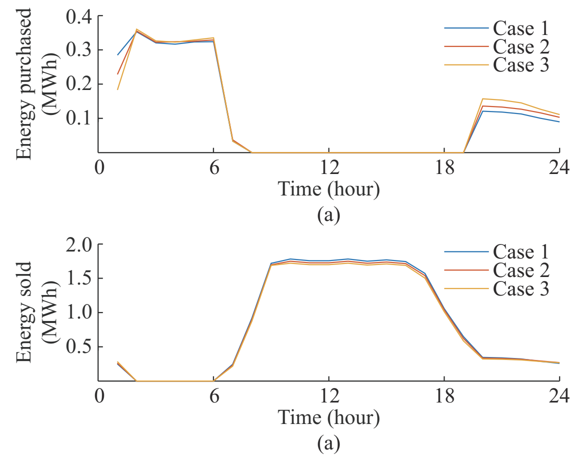

Fig. 7. Comparison of energy transactions of prosumers in each case. (a) Purchasing energy. (b) Selling energy.

B. Practical Test Network

In this study, a segment of the Tehran distribution network, representing an actual and tangible system, serves as the focal point for the analysis of the proposed model and algorithm [29]. The chosen segment is a 13-bus distribution network, mirroring the complexities and intricacies of a real-world distribution network. The network comprises 12 branches, with the slack bus strategically positioned at bus 1 and a base voltage set at 20 kV.

This carefully selected configuration provides a realistic foundation for evaluating the efficacy of the proposed algorithm in managing the dynamic interactions within a distribution network. The active and reactive peak loads within this distribution network are specified at 5.5 MW and 2.8 Mvar, respectively, encapsulating the operational characteristics of the system under consideration. Distributed generation resources are strategically embedded within the network, specifically at buses 5 and 11. These resources contribute to the complexity of the system, introducing variables that demand sophisticated management strategies to optimize their integration into the network. Crucially, prosumers are strategically positioned at buses 3, 6, 9, 12, and 13, representing key nodes in the distribution network. Prosumers in this context are multifaceted entities, embodying self-load components, PV resources, and battery ESS. This diverse composition of prosumers encapsulates the evolving landscape of energy consumers who actively engage in both consumption and production, contributing to the overall dynamism of the distribution network.

The simulation results generated through the proposed model and algorithm have undergone meticulous examination and comparison across various cases. These cases encompass a spectrum of conditions and factors, allowing for a comprehensive evaluation of the performance and adaptability of the proposed model. The diverse cases considered in the analysis include variations in prosumer behavior, changes in distributed generation dynamics, and impacts of different load scenarios on network performance. By scrutinizing and comparing these simulation results across multiple cases, this study aims to provide nuanced insights into the adaptability and robustness of the proposed model in addressing the intricacies of a real-world distribution network. The choice of the Tehran distribution network as the testbed for these analyses enhances the practical relevance of the study, ensuring that the findings are grounded in the challenges and dynamics encountered in actual urban power distribution systems.

Table III systematically details the results derived from an in-depth analysis of diverse cases.

TABLE III
COMPARISON OF OPTIMAL 24-HOUR OPERATION RESULTS OF EACH CASE IN PRACTICAL DISTRIBUTION NETWORK

Case	Energy loss (MWh)	The minimum voltage (p.u)	The maximum voltage (p.u)	Load shedding (MW)	Total electricity sale of prosumers (MW)	Total electricity purchase of prosumers (MW)	Peak load (MW)	CPU time (s)
1	0.26	0.95	1.044	0	96.0	13.4	1.00	4.66
2	0.24	0.95	1.033	0	95.0	12.5	0.95	4.91
3	0.21	0.95	1.020	0	94.5	12.0	0.90	4.94

The central theme of this study revolves around the transformative effects of integrating demand-side management into the studied model, with a pronounced positive impact observed across key network performance metrics such as energy losses, voltage stability, peak load, and the overarching objective function. A prominent trend emerges from the tabulated results, emphasizing the incremental improvements in network performance metrics with the progression of variable loads. This trend applies not only to the broader network, but also to individual prosumers. For instance, Case 1 manifests a significant difference of 82.6 MW between energy purchase and sale for prosumers. This disparity diminishes to 82.5 MW in Case 3. This reduction reflects more balanced and optimized energy exchange dynamics among prosumers, a direct consequence of the implemented demand-side management strategies. Examining energy losses over a 24-hour period further underscores the impact of load variations. In Case 1, energy losses amount to 260 kWh, but those of Cases 2 and 3 decrease to 240 kWh and 210 kWh, respectively. This trend highlights a clear correlation between load variations and the reduction in energy losses, emphasizing the effectiveness of demand-side management in minimizing energy wastage within the network. Voltage deviation, a critical indicator of network stability, showcases a similar pattern. In Case 1, voltage deviation is measured at 0.094 p.u., while in Cases 2 and 3, it diminishes to 0.083 p.u. and 0.07 p.u., respectively. This systematic reduction in voltage deviation illustrates the stabilizing influence of demand-side management, promoting optimal voltage levels within the network. Crucially, the integration of the load shedding cost function into the objective function of the demand-side management stands out as a significant aspect of the analysis. This strategic inclusion acts as a safeguard, ensuring that load shedding is avoided across all cases. This outcome not only aligns with the broader goals of minimizing disruptions but also serves as a testament to the efficacy of the proposed model in managing energy distribution, network load, and prosumer participation in a cohesive and harmonious manner. The findings from Table III collectively affirm the effectiveness of demand-side management strategies in achieving the intended objectives within the intricate dynamics of the modeled energy system.

C. 118-bus System

This subsection presents and analyzes simulation results for a distribution network consisting of 118 buses. It focuses on prosumers located strategically at various points within this network, specifically at buses 12, 18, 24, 31, 38, 45, 57, 59, 64, 69, 74, 79, 84, 88, 92, 93, 99, 105, 110, 115, and 117. These prosumers contribute to the network with diverse energy components including self-load, PV resources, and battery ESS. Incorporating these elements adds complexity to the simulation, enabling a more realistic portrayal of a distributed energy network [36].

Table IV provides a comprehensive overview of the transformative influence of integrating demand-side management into the proposed model.

TABLE IV
COMPARISON OF OPTIMAL 24-HOUR OPERATION RESULTS OF EACH CASE IN 118-BUS DISTRIBUTION NETWORK

Case	Energy loss (MWh)	The minimum voltage (p.u)	The maximum voltage (p.u)	Load shedding (MW)	Total electricity sale of prosumers (MW)	Total electricity purchase of prosumers (MW)	Peak load (MW)	CPU time (s)
1	1.200	0.9701	1.031	0	148.2	18.20	22.71	58
2	1.040	0.9713	1.024	0	145.6	18.22	21.57	67
3	0.887	0.9732	1.020	0	143.0	18.50	20.49	81

It systematically presents outcomes across various cases, emphasizing positive effects on key network performance metrics such as energy losses, voltage stability, peak load, and the overarching objective function. A notable trend emerges, highlighting incremental improvements in network performance metrics with variable loads, evident both across the network and at individual prosumers. For example, energy purchase and sale differentials decrease from 130 MW to 124.5 MW with a 10% load change, reflecting optimized energy exchange dynamics among prosumers due to demand-side management strategies implemented. Analysis of energy losses over a 24-hour period further underscores the impact of load variations, with reductions from 1200 kWh in Case 1 to 1040 kWh in Case 2 and 887 kWh in Case 3, respectively, indicating the effectiveness of demand-side management in minimizing energy wastage. Besides, the voltage deviation exhibits a similar pattern, showcasing systematic reductions with load variations. The integration of the load shedding cost function into the objective function of the demand-side management emerges as a significant aspect, ensuring load shedding avoidance across all cases and promoting cohesive energy distribution management. Overall, the findings from Table IV collectively confirm the effectiveness of demand-side management strategies in achieving intended objectives within the intricate dynamics of the modeled energy system.

D. Comparison

In this subsection, we systematically illustrate and substantiate the superior performance of the proposed algorithm when compared with various existing optimization algorithms. Through a comprehensive set of empirical analyses and benchmark evaluations, we aim to provide a nuanced understanding of how our algorithm outperforms its counterparts in terms of efficiency, convergence speed, and solution quality.

In order to validate the comparison with other selected algorithms, we ensure that equal conditions are maintained across the board, which includes using identical network data for all algorithms and utilizing the same computer system for execution. We also limit the number of iterations at a maximum of 100 for each algorithm to maintain consistency. Besides, we meticulously select optimal parameters for each algorithm. This task is accomplished through multiple iterations of execution for each algorithm, allowing us to fine-tune the parameters for optimal performance.

Table V is a comparison of the proposed algorithm with the GA, PSO, teaching-learning-based optimization (TLBO), Jaya, and gray wolf optimization (GWO) in 33-bus distribution network in Case 3.

TABLE V
COMPARISON OF PROPOSED ALGORITHM WITH OTHER ALGORITHM IN 33-BUS DISTRIBUTION NETWORK IN CASE 3

Algorithm	Convergence speed (number of iterations)	Energy loss (MWh)	CPU time (s)
Proposed	9	0.143	8
GA	58	0.163	79
PSO	36	0.161	56
TLBO	22	0.159	35
Jaya	17	0.157	16
GWO	29	0.155	25

As can be observed from Table V, the proposed algorithm shows a convergence in only nine iterations, which is significantly lower than the other algorithms. This indicates that the proposed algorithm reaches a solution much faster than the other algorithms. Besides, it can be observed that the proposed algorithm achieves the lowest energy loss of 0.143 MWh among all algorithms. This demonstrates the ability of the proposed algorithm to find a more efficient solution in terms of minimizing energy losses. The CPU time indicates how long the algorithm takes to run and produce results. The proposed algorithm completes its run in only 8 s, which is the fastest among all algorithms. This suggests that the proposed algorithm is not only faster in terms of convergence speed but also more efficiency in terms of computational time. In conclusion, the proposed algorithm demonstrates superiority over the other algorithms in all three compared metrics.

Figure 8 illustrates a comparison of convergence speed among five algorithms in the 33-bus distribution network. As can be observed, the proposed algorithm exhibits the most favorable convergence speed, achieving convergence within nine iterations while also minimizing energy loss to the greatest extent. Overall, Fig. 8 illustrates the superior efficacy of the proposed algorithm in minimizing energy losses within the 33-bus distribution network, requiring the fewest iterations to achieve this optimization.

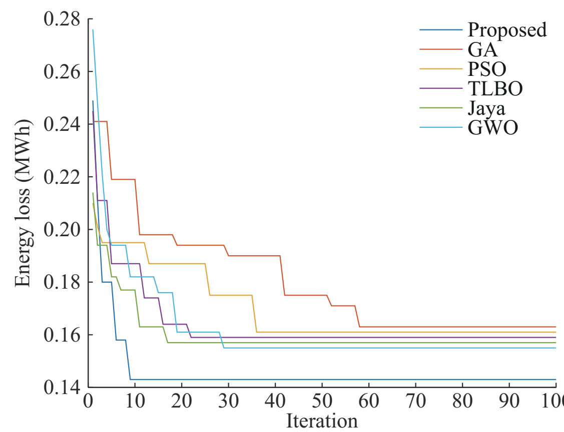

Fig. 8. Comparison of convergence speed of different algorithms in 33-bus distribution network.

E. Analysis of Scenario-based Uncertainty

A comprehensive analysis of the impact of scenario-based uncertainty on energy losses and CPU time across different test networks in Case 3 is provided in Table VI.

In terms of energy losses, varying the number of scenarios yields mixed results. For the 33-bus distribution network, energy losses fluctuate slightly. For the practical distribution network, energy losses remain relatively consistent. For the 118-bus distribution network, energy losses decrease as the number of scenarios decreases, indicating that fewer scenarios result in more efficient energy management, with the lowest energy losses observed in the case of one scenario.

Regarding CPU time, the trend is more consistent across all test networks. As the number of scenarios decreases, the CPU time required to solve the optimization problem decreases significantly. This suggests that reducing scenario complexity facilitates faster problem-solving and higher computational efficiency. This pattern is particularly evident in the 118-bus distribution network, where the CPU time decreases dramatically from 214 s in the case of 100 scenarios to 45 s in the case of one scenario.

Overall, the analysis underscores the importance of considering scenario-based uncertainty in energy management optimization. While the impact of scenario complexity on energy losses may vary depending on the network configuration, reducing scenario complexity consistently leads to improved computational efficiency. This highlights the necessity for careful consideration of scenario selection in energy management decision-making processes to balance accuracy with computational resources.

TABLE VI
ANALYSIS OF IMPACT OF SCENARIO-BASED UNCERTAINTY IN CONSIDERED TEST NETWORKS

Number of scenarios	33-bus distribution network		Practical distribution network		118-bus distribution network	
	Energy loss (MWh)	CPU time (s)	Energy loss (MWh)	CPU time (s)	Energy loss (MWh)	CPU time (s)
1	0.141	5	0.20	3	0.882	45
50	0.143	8	0.21	5	0.887	81
100	0.142	21	0.21	16	0.889	214

IV. CONCLUSION

In this paper, an MISOCP model is proposed for optimal load and energy management in active distribution networks by considering prosumers. A multi-objective function is designed to improve grid performance and the profitability of prosumers, taking into account grid constraints and the uncertainty of PV resources along with ESSs. To solve the proposed model, a powerful hybrid algorithm called MPSO-GA is chosen, which has a high convergence capability for solving difficult problems. Different distribution networks are used for the analysis of the proposed model and algorithm in different cases. The simulation results demonstrate that the proposed model can reduce energy losses by up to 26.2% and reduce the voltage deviation by up to 17.72%, while also increasing the profit of prosumers based on PV and ESS. For future research, the following aspects are suggested.

1) Modeling a multi-level model to reduce costs and increase network flexibility so that distribution network objectives are formulated at one level and prosumer objectives are formulated at another level.

2) Modeling power-to-gas systems to convert excess energy from prosumers into natural gas and sell it to the gas utility.

3) Modeling of distributed flexible AC transmission system (D-FACTS) devices to improve network indicators in the presence of prosumer power changes in the presence of renewable energy resources.

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