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Developing Hybrid Demand Response Technique for Energy Management in Microgrid Based on Pelican Optimization Algorithm

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A R T I C L E I N F O

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A B S T R A C T

This paper proposes a new application of Pelican Optimization Algorithm (POA) for optimal Energy Management (EM) in Microgrid (MG) considering Demand Response program (DRP). To maximize the MG operator (MGO) benefit and to reduce the overall operating cost, including the cost of conventional generator fuel and power transaction cost, multi-objective optimization is formulated. To achieve the optimal operation of the MG, a Hybrid DRP is proposed, based on Incentive-based Demand response (IDR) to reduce the peak load and to ensure MG reliability. Reliability is achieved by applying the Hybrid technique to encourage customers to reduce their consumption during peak hours. Applying the conventional IDR (CIDR) for optimal operation leads to customers curtailments to be in off-peak hours. Also instead of using predetermined or specifying fixed hours as peak hours, the proposed hybrid DR technique is a dynamic technique based on the load profile and the average load value. Furthermore, Peak reduction percentage (PRP) was employed to show MG's reliability enhancement. Two distinct MG test systems are examined; the effectiveness of the proposed hybrid dynamic demand response (HDDR) with the proposed POA is demonstrated by comparing its simulation results to those of well-known metaheuristics and newly developed algorithms. According to HDDR with POA technique results, a total reduction in peak hours' load is about 14.6% in the first test system and 7.6% in the second test system. The results indicate that the POA has superiority in solving the EM problem.

1. Introduction

1.1. Motivation

The drastic increase of global energy consumption is the main reason of the fast depletion of fossil fuels and increasing greenhouse gas emissions. Also, the complete reliance on traditional energy sources to meet energy demand is seen an inefficient solution. Therefore, Renewable Energy Sources (RES) (such as solar, wind, biomass, geothermal, and hydro, etc.) being non-depleting abundant clean sources emerged as a potential alternative for fossil fuels powered sources and it has shown a mushrooming growth in the last couple of decades. However, the intermittent nature of renewable energy resources poses great challenges on their large scale integration. This paved the road to Microgrid as an enabling means for integration more RES through.

Typical MG is formed by the integration of small-scale Distribution Energy Recourses (DERs); typically RESs non-renewable sources, and Energy Storage Systems (ESS) with responsive and non-responsive loads [1–4]. In MGs with RESs, the demand side is required to have arrangements to cope with the variability and intermittency at the supply side. Hence, Demand Side Management (DSM) becomes crucial for enabling RES integration. DSM can be defined as a comprehensive method that manages the customers demand through various strategies [5]. Also, peak load hours last only for few hours in the daily, the peak to average ratio of demand in electric power systems is high [6]; in order to supply the peak loads, a high increase in the investment should be made, which results in an increase in the electricity cost. To solve this challenge also DSM should be considered [7]. DSM strategies include Demand Response (DR) and Energy efficiency. Energy efficiency is the process of reducing energy consumption while performing the same duties or tasks

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Table 1
Summary of the relevant literature.

Reference	Formulation	DR	Peak reduction	MGO benefit	PV and wind	Objective Function	Peak reduction technique
[13]	Robust optimization method	✓	✘	✘	✓	single	-
[14]	Metaheuristics algorithms	✓	✘	✘	✓	Multi	-
[15]	MILP	✓	✘	✘	✓	Multi	-
[16]	augmented Epsilon-constraint method	✓	✘	✘	✓	Multi	–
[17]	PSO	✘	✘	✘	✓	Multi	-
[19]	MILP	✓	✘	✘	✓	Single	-
[20]	GA optimization	✓	✘	✘	✓	Multi	-
[21]	DRL	✓	✘	✘	✓	Multi	-
[23]	GA optimization	✓	✘	✘	✓	single	-
[24]	MILP	✓	✘	✘	✓	Single	-
[25]	MILP	✓	✘	✘	✓	Single	-
[26]	AIMMS	✓	✘	✓	✓	Multi	-
[27]	PSO	✓	✘	✘	✓	single	-
[28]	NLP	✓	✘	✘	✓	Multi	-
[29]	GA optimization	✓	✘	✘	PV only	Single	-
[30]	PSO	✓	✓	✓	✓	Multi	Pre-specified
[31]	PSO-Fuzzy	✓	✓	✓	✓	Multi	Pre-specified
Proposed	POA	✓	✓	✓	✓	Multi	dynamic

with the same level of quality [8]; whereas DR encourages the customer to modify their consumption in response to an incentive payment. Further subcategories of DR include Incentive-based DR (IDR) and Price-based DR (PDR). In PDR, customer prices are fluctuated according to operating hours. For example, high prices at peak, medium for medium consumption, and low prices for the off-peak period, while in the IDR, the customer gets an incentive based on the quantity of electricity curtailed [9]. IDR is further classified into four groups: load curtailment, direct load control, demand bidding, and emergency demand reduction [9].

1.2. Related Work

Recently, MGs has gained high popularity; In MG powered by RESs with their intermittent nature, the integration of dispatchable energy sources powered by fossil fuel helps in enhancing the reliability [10]. To get the maximum benefit from MG's resources, MG resources are managed in a way that maximize the utilization of RESs and at the same time ensure an acceptable level emission levels. MG energy management has recently gained great attention in research [11–17]. The effectiveness of the DR in solving economic and environmental problems is studied in [18,19]. In [20], techno-economic performance comparison and optimal sizing for the MG sources considering the DR using Genetic algorithm(GA)optimization were studied; where different sizing strategies for residential customers based on time-of-use DR Strategies. In [21] optimal scheduling for the MG with utilization of DRP to increasing the consumers' comfort index has been proposed. For lowering the overall generation cost in MG, [22] proposed a dynamic control system with intelligent controllers depend on the deep reinforcement learning (DRL) technique for the optimal operation for each MG independently with bottom-up Energy internet(EI) architecture and data-driven strategy. Significant effort has been made to regulate the energy consumption of an MG by employing the DR to reduce the operating cost [23–26] or to maximize the MGO cost [26,27]. In [23], a genetic algorithm is embedded with the Energy Management System (EMS) to reduce the operating cost. In [24], a Mixed integer linear programming (MILP) is used for Multi-Microgrid. The optimal and safe operation of MG using multi-stage hierarchical EM is proposed in [25]. Authors in [26] proposed an IDR program to solve a multi-objective problem to reduce the cost and environmental effect using an interactive modeling method; the IDR model is solved by The Advanced Interactive Multidimensional Modelling System (AIMMS). In [27], Particle swarm optimization (PSO) is used to maximize the profit of the customers using PDR considering fixed and dynamic pricing strategies. Multi-objective problem to maximize the MGO benefit and reduce the operation cost solved using non-linear programming (NLP) using CPLEX in [28]A genetic algorithm is used in [29] for economic dispatch for the MG resources with considering the DR.

As mentioned above, the DR strategies have their advantage in lowering operational costs, minimizing pollutant emissions, and enhancing MGO benefits. The efficiency of the DRP has been proposed in the literature using a variety of approaches. Although environmental and economic concerns are important gradients of MG's optimal operation, peak load constraints must also be addressed. When evaluating the optimum energy management problem of an MG, there is an obvious requirement to assure system security even at peak time load while assuring environmentally friendly and economic operation. Also, during peak-demand hours, the generating units with lower emissions amounts have already been completely loaded, and those with higher emissions must be commissioned. As a result, DRP used to reduce the peak-hours load help in reducing the level of emissions [9]. In [30,31], hybrid demand response is proposed to enhance MG reliability, but it used fixed incentives or prices during the pre-specified peak period without considering the different load profiles for each day. Table 1 illustrates a comparative analysis of the relevant literature work.

The global optimum solution is the most fundamental optimum solution for an optimization problem. The solutions offered by optimization algorithms, on the other hand, are not always the same as the global optimum. Be a result, the solution achieved by optimization algorithms is referred to as quasi-optimal [32]. In addition, there are no metaheuristic optimization algorithms capable of solving all optimization problems, in accordance with the No-Free-Lunch (NFL) theorem [33]. These two reasons motivate the researcher to propose new optimization techniques to create better quasi-optimal solutions that are closer to the global optimal. Also, these are the main inspiration for us to apply a newly developed optimization technique, the newly-developed Pelican Optimization Algorithm (POA) [34], to solve the EM problem in MGs .

1.3. Contribution

The objective of this paper is to propose an energy management strategy using a HDDR strategy, which is proposed to improve the MG's reliability by primarily reducing the peak-load demand. The viability of our proposed HDDR technique was determined by comparing the peak load percentage (PRP) value to our scheme's advantages. MG's EM problem is solved by implementing the newly-developed POA [34].

Following is a summary of the major contributions of this paper:

- Implementing a newly proposed technique to reduce the MG's operating cost, increase the MGO benefit and enhance MG's reliability through peak-load reduction.

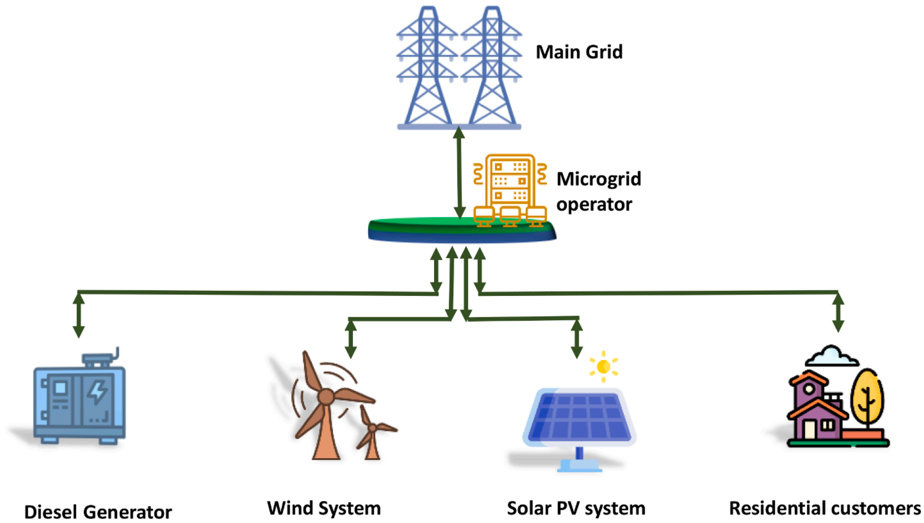

Figure 1. Grid-Connected MG Scheme with DR model.

- Proposing a new technique for peak load reduction, called hybrid dynamic demand response (HDDR), which considered conventional fixed prices IDR (CIDR) and peak-based variable prices IDR (PIDR) based on the load profile and the average load value.
- Proposing a new application for a recent optimization technique, POA, to solve Microgrids' EM problem considering demand response. And Comparing the performance of the proposed HDDR, and the results of CIDR.
- The peak reduction percentage (PRP) factor is employed to demonstrate the effectiveness of the proposed HDDR technique in enhancing the MG reliability.

1.4. Paper organization

The remaining parts of this paper are structured as following: Section 2 presents the mathematical model for MG with demand response. Section 3 presents a formulation of the EM problem. The proposed HDDR strategy is dissuaded in section 4 . Section 5 presents the fundamentals of the optimization algorithm used to solve the EM. Section 6 presents the simulation results obtained. The paper is concluded and the future work is mentioned in Section 7.

2. Grid-connected Microgrid overall scheme

The overall scheme of the proposed Grid-connected MG is shown in Figure 1. In this work, MG consists of renewable energy sources such as photovoltaic (PV) generator source and wind turbine (WT) generator source; conventional diesel Engine (CDE) sources; and consumer with demand response (DR) model

2.1. Modeling Grid-connected Microgrid

As shown in Figure 1, there is a connection between the main grid and the MG, and it is assumed there is a power transaction between them. So the power can be either bought or sold to the main grid.

2.2. Modelling of WT

Wind power is probabilistic in nature; WT's generated power depends on the tower height and wind speed. Wind speed at desired hub height can be obtained as [35] :

$$v_{hub_t} = v_{ref_t}\left(\frac{h_{hub}}{h_{ref}}\right)^{\alpha} \tag{1}$$

Where v_{ref_t} is the wind speed (hourly) at the reference height h_{ref}, α is the power-law exponent, which usually is in the range between $\frac{1}{4}$ and $\frac{1}{7}$; and v_{hub_t} is the hourly speed of the wind at the desired hub height h_{hub}.

The expected output power from WT is calculated as [36]:

$$P_w = \begin{cases} 0 & v \le v_{cut-in} \text{ and } v \ge v_{cut-out} \\ \frac{v^2 - v_{ci}^2}{v_{nom}^2 - v_{ci}^2}.P_{nom} & v_{cut-in} \le v \le v_{nom} \\ P_{nom} & v_{nom} < v \le v_{cut-out} \end{cases} \tag{2}$$

Where P_w and v denoting output power and wind speed; Which is based on wind turbine's rated power (P_{nom}), v_{nom} the rated speed, $v_{cut-out}$ The cut-out wind speed, and v_{cut-in} the cut-in speed.

2.3. Solar power modelling

The hourly electric power generated from a PV generator for a given area can be given as [37]:

$$P_{st} = \eta_{pv} A_c I_{Pv_t} \tag{3}$$

Which is based on A_c is the area of PV array, (η_{pv}) is soalr array efficiency and it varies with the ambient temperature and incident solar irradiation on the PV array I_{Pv_t} (kW h/m^2).

2.4. Modelling of CDE and load

CDE is a significant generating source in the MG that the operator may adjust flexibly. When the MG cannot meet the load demand from RESs, the CDEs serve as a supplementary generation source to meet the load. The fuel cost for conventional DEs ($C_i(P_{i_t})$) is represented by a quadratic model as follows [37]:

$$C_i(P_{i_t}) = a_i p^2_{i_t} + b_i P_{i_t} \tag{4}$$

Where, $a_i$and $b_i$are fuel cost coefficients for any conventional generator i.

In order to solve the MG optimization problem, an accurate model of the load is required. Typically, the load is calculated as the total of individual customer loads. However, in this work, the customers are categorized based on their willingness to participate in DRP.

2.5. Modelling Incentive Demand Response

If we donate the cost customer incurred as $C(\theta, x)$; where θ is the customer type which is an indication of his willing to the participation in DRP, customer type value varies between 0 and 1 that the customer who with the most willing g have this value as 1, and the lower willing customer has a value of 0; and x represents the customer power curtailment (or reduction) in (KW or MW). The demand response complete model is discussed in the following equations eqs. (5)-((9)) [26].

The customer cost function can be expressed as:

$$C(\theta, x) = k_1x^2 + k_2x(1-\theta_j) \tag{5}$$

Where k_1, and k_2 are cost coefficients.

So the customer's benefit is mathematically expressed as:

$$F_1(\theta, B, x) = B - C(\theta, x) \tag{6}$$

Based on Equation (6), the customer will reduce his consumption in the case of his benefit function in DR $F_1 \geq 0$ with B represents total incentive that customers will receive for consumption reduction. Also, MG benefit can be expressed as:

$$F_2(\theta, \lambda, x) = \lambda x - B \tag{7}$$

Where λ is the cost of power interruption from a particular customer, power interruptibility can be calculated from optimal power flow analysis [38].

Based on Customers' Contract formulation in [38], if B_j is the incentive that customer get, so based on customer cost function (Equation (5)) so benefit for customer J is computed as:

$$U_j = B_j - \left(k_1x_j{}^2 + k_2x_j(1-\theta_j)\right) \text{ for } 1, 2, \ldots\ldots J \tag{8}$$

Moreover, the whole MGO benefit is calculated as:

$$U_0 = \sum_{j=1}^{J} \lambda_j x_j - B_j \tag{9}$$

3. Formulation of the Energy Management Problem

As discussed previously, MG in this paper consists of several DG types, including CDE, RESs, and loads with a DRP. The main objective of the EM in MG is the optimal operation of energy sources in the MG in order to distribute the load among the available generating sources in an economical manner. For solving Multi-objective optimization problem, POA is implemented to select the most optimal power generation from the different sources. The following sub-section presents the mathematical formulation of two distinct objective functions with the corresponding constraints.

3.1. Objective function

In this paper, the objective function is a multi-objective first objective as follows: (a) minimizing the operating cost function $f_1(x)$, which is composed of two components: the CDEs' generation cost and the cost of electricity transactions; and (b) maximizing MG operator benefit $f_2(x)$ by considering the DRP in EM problem.

a) Operating cost function:

This objective function mathematical formulation can be described as follow:

$$\min f_1(x) = \min \sum_{t=1}^{T}\sum_{i=1}^{I} C_i(P_{i_t}) + \sum_{t=1}^{T} C_g(P_{g_t}) \tag{10}$$

where P_{g_t} is the amount of transacted power between MG and main grid at any time t; power purchasing is based on Locational Marginal Prices (LMP's) (γ_t) [39] .Therefore, power transactions cost $(C_g(P_{g_t}))$ can be calculated as [26]:

$$C_g(P_{g_t}) = \left\{ \begin{array}{c} \gamma_t \times |P_{g_t}| \text{ From main grid} \\ 0 \text{ no transaction} \\ -\gamma_t \times |P_{g_t}| \text{ from MG} \end{array} \right\} \tag{11}$$

a) MG operator benefit

In this paper, the IDR MGO benefit (9) is extended for the whole optimization interval T (one day) so it will be more cost-effective. Then F_2 function is modified so the second objective function is mathematically expressed as:

$$\max f_2(x) = \max \sum_{t=1}^{T}\sum_{j=1}^{J} \lambda_j x_j - B_j \tag{12}$$

Accordingly, the mathematical model of the objective function for MG management based on the weighted sum is expressed as:

$$\min w\left[\sum_{t=1}^{T}\sum_{i=1}^{I} C_i(P_{i_t}) + \sum_{t=1}^{T} C_g(P_{g_t})\right] + (1-w)\left[\sum_{t=1}^{T}\sum_{i=1}^{I} B_{j,t} - \lambda_{j,t}x_{j,t}\right] \tag{13}$$

3.2. Constraints

3.2.1. Power Balance Constraints [26]

$$\sum_{i=1}^{I} P_{i_t} + P_{g_t} + P_{wt} + P_{st} = D_t - \sum_{j=1}^{J} x_{j,t}. \tag{14}$$

Where D_t is the initial load demand and $x_{j,t}$ is customer j power curtailment at time t.

3.2.2. Generation constraints [26]

$$P_{i_{min}} \leq P_{i_t} \leq P_{i_{max}} \tag{15}$$

$$-DR_i \leq P_{i_{t+1}} - P_{i_t} \leq UR_i \tag{16}$$

Where UR_i and DR_i are the maximum ramp up and ramp down rates for generator i. $P_{i_{max}}$ $P_{i_{min}}$ are the maximum and minimum $(P_{i_{min}})$ limits..

3.2.3. Power transaction Constraints [26]

$$P_{g_{max}} \leq P_{g_t} \leq P_{g_{max}} \tag{17}$$

3.2.4. Demand response constraints

Based on (8), the customer benefit is extended for the complete time horizon(one day) to be cost-effective; this constraint is formulated and expressed as [26]:

$$\sum_{t=1}^{T} B_{j,t} - \left(k_1x_{j,t}{}^2 + k_2x_{j,t} - k_2x_{j,t}\theta_j\right) \geq 0 \tag{18}$$

Constraint (19) describes the allowable level of power curtailment for customer j as:

$$\sum_{t=1}^{T} x_{j,t} \leq CM_j \tag{19}$$

Where CM_j is his power curtailment limit.

$$\sum_{t=1}^{T}\sum_{j=1}^{J} B_{j,t} \leq UBL \tag{20}$$

Where UBL is the daily MG budget upper limit [26].

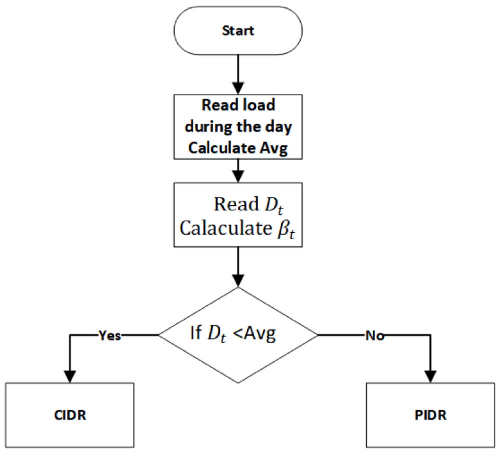

Figure 2. The proposed HDDR flowchart.

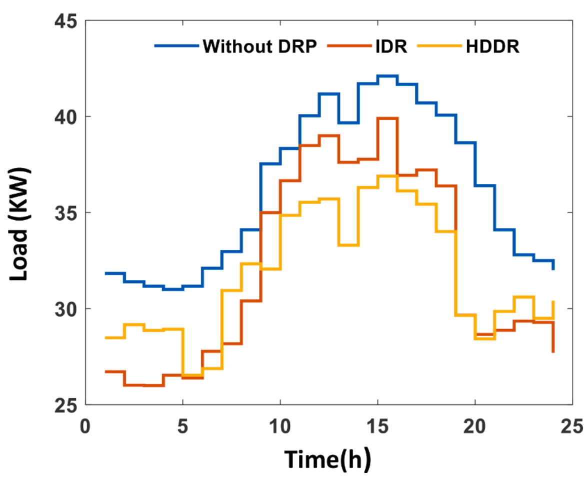

Figure 3. Initial and final load with IDR and with proposed HDDR.

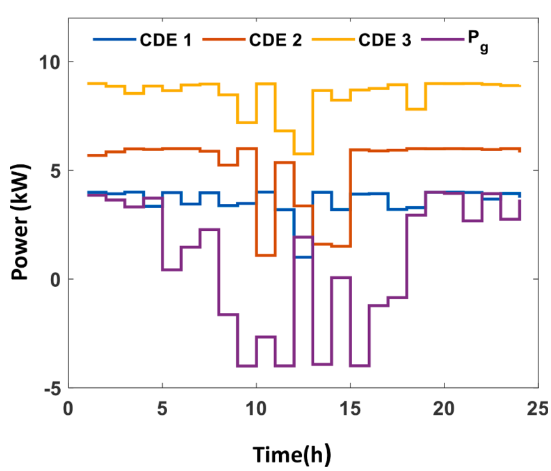

Figure 4. Conventional DEs output and power transacted with the grid (Test system1).

4. Proposed Hybrid Dynamic Demand Response Strategy

4.1. The proposed technique description

To ensure the MG reliability and enhance the shortcoming of conventional and predetermined IDR programs, which incorporates fixed incentive rates, we propose the HDDR technique. This strategy will provide system flexibility to maximize the usage of available RES, such as wind and solar RESs, which are effective at certain times during the day. For this purpose, the PRP is utilized to quantify the particular advantages of the HDDR strategy's implementation. The proposed HDDR is based on applying either CIDR or PIDR based on the load value at this time slot. As shown in Figure 2 the at the time where the demand is more than the average value, an incentive demand response program is applied; while in the case of peak period (load is higher than the average value), a PIDR is applied; where the customer gets a larger payment for his curtailment to reduce his consumption at the peak hours period for enhancing the reliability of MG.

And Customer incentive

$$y_{Bj} = (1 + \gamma\, \beta_t) y_{ij\_\min} \tag{21}$$

With

$$\beta_t = \frac{D_t}{D_{peak}} \tag{22}$$

Where y_{ij_min} is the minimum incentive a customer can receive to ensure his benefit, γ is a scaling factor; it is used in this paper as 0.2. From Equations (21) and (21), it can be noted that the incentive that customers get by HDDR technique during peak hours not only depends on the level of curtailment but also on total hourly demand compared to the peak load.

4.2. Peak Load Reduction

In the literature there are different metrics or indexes to evaluate the peak load reduction or shaving. The simplest metric for the peak load reduction is the load factor [40,41]. Where only the peak load value is compared to the average load value. Another indexes is presented in [42]; However the peak hours are assumed to be fixed hours. Peak load reduction is the main objective of implementing the HDDR program, which offers a larger incentive to the customer during peak periods to encourage them to curtail more power during this period. To demonstrate the efficacy of the proposed technique, we employ a PRP indicator that calculates how the load during peak is reduced compared to the initial peak load with the implementation of the HDDR program. Not only the peak load value, but this indicator is extended to compare the total load during peak hours with and without the proposed HDDR.

Peak Reduction percentage (PRP) can be calculated as:

$$D_{peak\_wo} = \sum D_{t\_peak} \tag{23}$$

$$D_{peak\_w} = \sum D_{peak,t} - \sum_{j=1}^{J} \sum_{t=1}^{T} x_{j,t\_paek} \tag{24}$$

$$PRP = \left(\frac{D_{peak_{wo}} - D_{peak_{w}}}{D_{peak_{wo}}} \right) * 100 = \frac{\sum_{j=1}^{J} \sum_{t=1}^{T} x_{j,t\_paek}}{D_{peak_{wo}}} * 100 \tag{25}$$

Where x_{j,t_paek} is the customer j curtailment at any time t in the peak period regions.

5. Solution method

5.1. Description

This algorithm, Pelican Optimization Algorithm (POA), is a new stochastic nature-inspired optimization technique [32], which is considered to have better exploration and exploitation in the searching for global optimum [43]. Recently, swarm-inspired algorithms have received the greatest traction [44]. POA is inspired by the hunting strategy and behavior of pelicans. Pelicans often hunt together in groups. The pelicans, after identification of their food source (pray) the

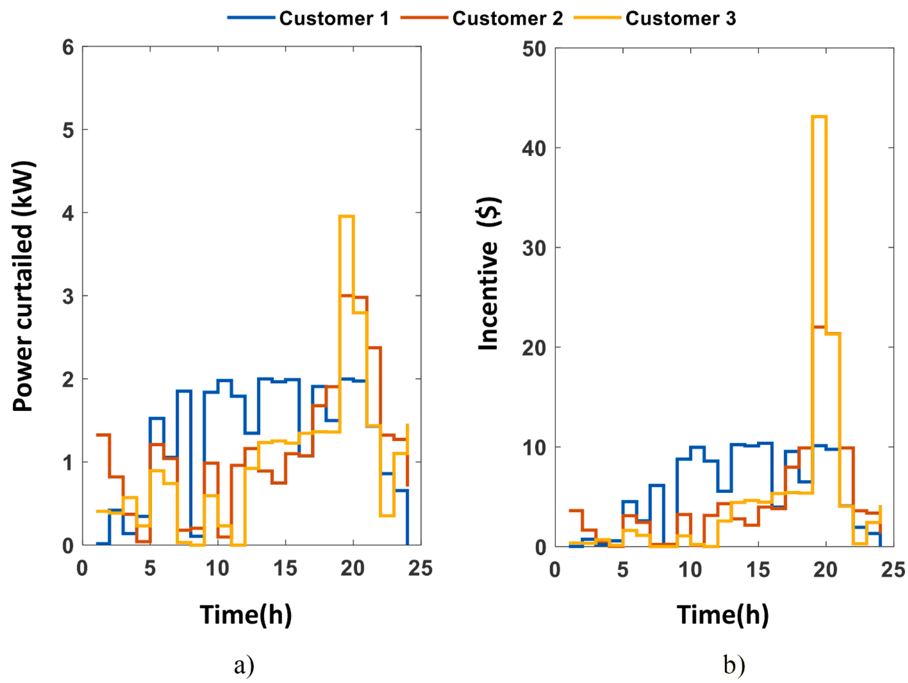

Figure 5. For Test system 1: a) Customers' power curtailment (kW)and b) customer incentive ($).

Table 2
cost breakdown for the three optimization techniques (MG test system 1).

	IDR			HDDR		
	PSO	INFO	POA	PSO	INFO	POA
Total Conventional Power (kW)	441.93	410.35	433.75	395.93	407.82	410.35
Total Conventional Power Cost ($)	221.25	242.98	256.13	226.12	237.45	242.98
Total Transferred Power (kW)	52.93	4.17	-13.52	44.386	8.42	4.17
Total transferred power Cost ($)	264.65	20.88	-67.64	221.93	42.10	20.88
Total Customer Incentive ($)	313.71	436.92	351.75	409.56	428.71	436.92
Total Cost ($)	799.62	684.08	594.36	857.61	708.26	700.79

location; dive, then spread their wings to force their pray to move to the surface of the water and shallow water so pelicans can attack prays easily. The main steps of the POA can be described as follows:

- ***Initialization:*** POA is a population-based algorithm in which every pelican member is considered a candidate solution. The optimization process is started by randomly initialization to every member in the population using the following Equation:

$$x_i = LB + rand * (UB - LB)\ i = 1, 2, \ldots\ldots, N \tag{26}$$

Where N is the number of population members, x_i is the value of the candidate solution, and *rand* is a random vector in the interval [0, 1].

Then those initial candidates' solutions are used to evaluate the objective function for the given problem. Then objective function vector is calculated.

The behavior of pelicans' hunting strategy in attacking their food source is simulated to update the candidate solution. This process is simulated in two phases as follows:

- ***Phase 1 Moving towards food source (Exploration phase):*** This phase simulates the strategy of pelicans in scanning the search space for food source identification. After identifying their prey, the Pelicans start moving toward the prey area. One important feature of POA is randomly generating the pray location, increasing exploration power. The new status of the ith pelican candidate solution on phase is simulated mathematically as in 0:

$$x_i^{new\_1} = \begin{cases} x_i(t) + rand.\left(x_p - I.x_i\right), & ifF\left(x_p\right) \le F(x_i) \\ x_i(t) - rand.\left(x_p - I.x_i\right), & else \end{cases} \tag{27}$$

Where I is a randomly generated vector which has a value of 1 or 2, x_p is the randomly generated location of prey and $F(x_p)$ is the value of its objective function. Then an update to the solution based on the new position is performed as :

$$x_i(t+1) = \begin{cases} x_i^{new\_1}, & ifF(x_i^{new\_1}) \le F(x_i) \\ x_i(t), & else \end{cases} \tag{28}$$

Table 3
peak load reduction comparison for MG and MGO MG benefit be test system 1.

Peak load without DRP(D_{peak_wo})(kW)	478					
DRP	IDR			HDDR		
Technique	PSO	INFO	POA	PSO	INFO	POA
Peak DR DRP ($D_{peak\_w)}$) (kW)	443.2010	436.9815	424.08	419.2785	415.22	408.2782
PRP (%)	7.28	8.58	8.9	12.28	13.1	14.6
MG benefit ($)	15	22	50	10	23	30

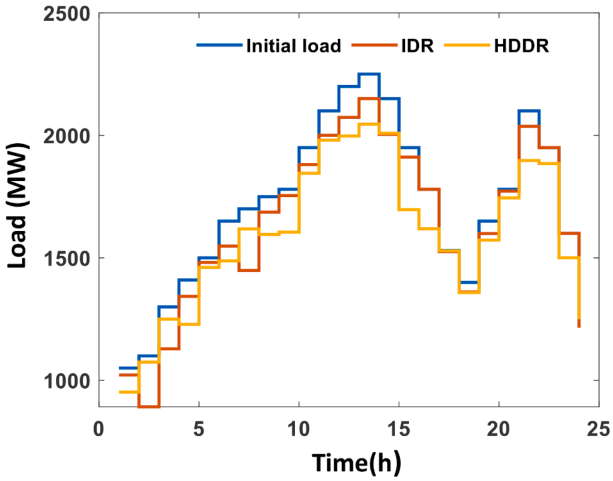

Figure 6. Initial and final load with IDR and with proposed HDDR.

-Phase 2: Winging on the water surface (exploitation phase): In this phase, pelicans start to spread their wings on the water's surface to let pray move upwards. Which help in increasing the ability of local search; the new status of the ith pelican candidate solution on phase 2 is mathematically modelled as:

$$x_i^{new\_2} = x_i(t) + R.\ (1 - t/T\ ).(2.rand - 1)x_i(t), \tag{29}$$

Where t is the current iteration, T is the maximum number of iterations, and R is a constant equal to 0.2. Then an update to the solution based on the new position is performed as

$$x_i(t+1) = \begin{cases} x_i^{new\_2}, & if F(x_i^{new\_2}) \le F(x_i) \\ x_i(t), & else \end{cases} \tag{30}$$

Where $F(x_i^{new\_2})$ is the objective function value of $x_i^{new\_2}$ candidate solution.

6. Results

To validate the feasibility and effectiveness of the proposed HDDR program with POA in solving the energy management problem in MG, different test systems for grid-connected MG consisting of DG units and customers considering DRP is simulated using MATLAB 2021b on operating system has the following specification a 2.9-GHz i7 with 8-GB of RAM. MG is supplied with PV modules and a WT unit with varied ratings in each test system. In addition, CDEs are employed; a typical representation of a simulated MG is depicted in Figure 1. MG EM problem is solved using the different DRPs in two cases in two different MG test systems. The first case uses conventional IDR, while the second case, the proposed HDDR, is implemented. The superiority of the proposed HDDR technique using POA in solving the EM problem compared to the well-known PSO [45] technique and newly-developed INFO [46] technique is proven.

6.1. *Microgrid test system 1 (First case study)*

Based on the grid-Connected MG Scheme shown in Figure 1, the first MG test system (case study) is a small MG comprised of one PV and one WT generator, three CDE units, and three residential customers with DRP. CDEs parameters, initial demand, power interruptibility for each customer (($\lambda_{j,t}$), and hourly output power values of WT and PV generators are adopted from Ref. [26]. A day-ahead (24 h) EM problem is solved by the proposed technique using conventional IDR is applied to the EM problem, and the proposed HDDR program; the initial load and load after applying the different techniques are shown in Figure 3., It can be noted that in the case of using IDR, as the objective is to maximize the MGO benefit, most of the customers' curtailment happens in times where there is no or small sharing from renewable sources; while in the second case (HDDR) the total demand is much reduced on the peak periods (more than the average) higher than that in out-of-peak periods. Using POA, the total demand reduction in the first case is 98.67kWh with a peak period load of 478 kWh (above average); 53.91 kWh only is curtailed in the peak period, while around 44.67 kWh reduction on load consumption in the other periods. For the HDDR case, the total demand reduction is 104.37 kWh with 69.72 kWh curtailed during the peak period, while only around 34.64 kWh reduction on load consumption in the other periods. Due to the implementation of the HDDR, most curtailment occurs in the peak period. These results indicate that using the HDDR program achieves higher load reduction while the MG reliability is maintained. The optimal scheduling of the CDEs generation in addition to the power transacted with the main grid (P_{g_t}) are depicted inFigure 4; before the WT and PV generation period, the load is fed either from CDEs or the power is bought from the main grid. While in the

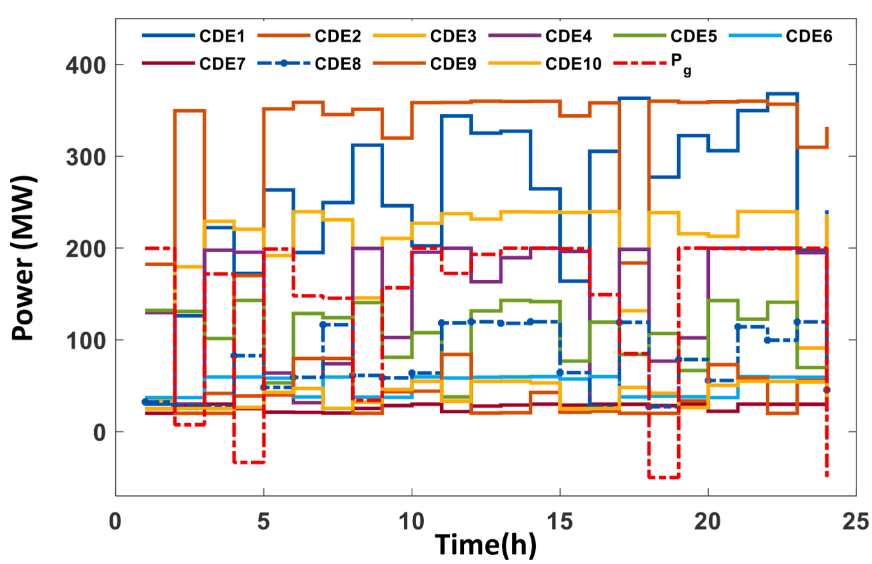

Figure 7. Conventional DEs output and power transacted with the grid (Test system1).

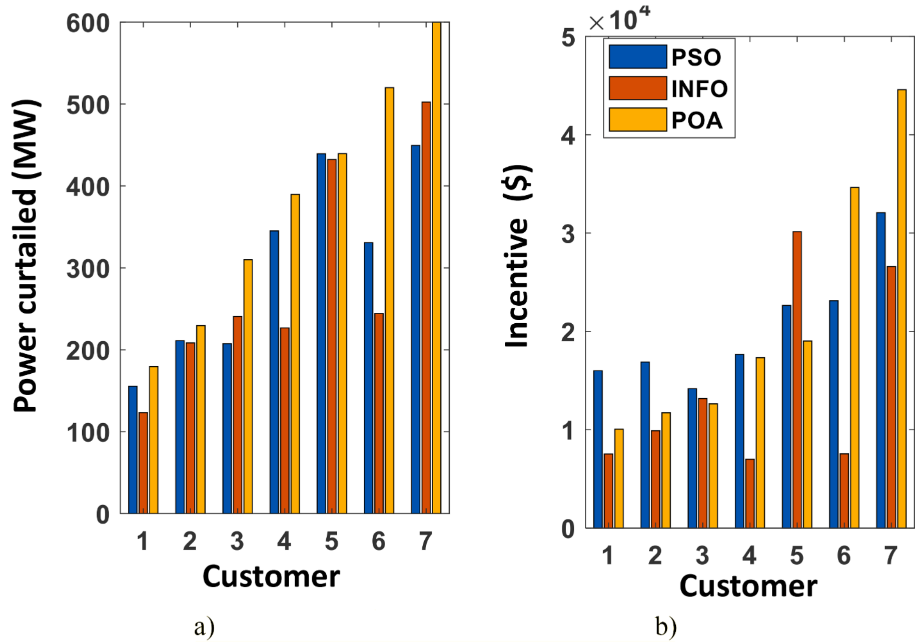

Figure 8. For Test system 2: a) Customers' power curtailment (MW)and b) customers incentive($)

Table 4
cost breakdown for the three optimization techniques (case study2).

	CIDR PSO	INFO	POA	HDDR PSO	INFO	POA
Total Conventional Power (MW)	28142	24986	25792	26951	24880	30355
Total Conventional Power Cost ($)	616430	533410	555460	591220	543840	560000
Total Transferred Power (MW)	6527.1	8936.1	7960.5	7261.2	9493.2	33267
Total transferred power Cost ($)	48953	67021	59704	54459	71199	21624
Total Customer Incentive ($)	94497	13670	14174	142520	117880	149992
Total Cost ($)	759880	639087	629338	788199	732919	731616

Table 5
peak load reduction comparison and MG benefit for MG test system 2.

Peak load without DRP (D_{peak_wo})(MWh)	23740					
DRP	IDR			HDDR		
Technique	PSO	INFO	POA	PSO	INFO	POA
Peak DR DRP (D_{peak_w}) (MWh)	23000	22714	22376	22207	22501	21920.72
PRP (%)	3.1	4.32	5.74	6.45	5.22	7.66
MG benefit ($)	2200	2000	3000	1800	1750	2025

period where RESs produce their maximum power the MG often sell the extra power to the main. Figure 5 displays the power reduction from each customer and the incentive they receive; it can be seen that the incentive during peak periods is higher than during off-peak periods. Cost breakdown comparison using the different techniques is detailed in Table 2; the results from this table indicate that the lowest cost is achieved using the proposed POA technique in the two studied cases (IDR and HDDR). Also, Table 3 shows a comparison between the different techniques in terms of PRP; POA technique achieved the highest PRP in the two studied DRP techniques. Looking to the MGO benefit in Table 3; using POA MGO benefit is the largest in the IDR and HDDR.

6.2. Microgrid test system 2 (second case study)

Based on the grid-Connected MG Scheme shown in Figure 1 test system 2 is a bigger MG comprised of an aggregated model for PV (10 units) and aggregated WT generators (ten units), ten CDE units, and seven aggregated residential customers with DRP. The CDEs parameters, customer, customers data, initial demand and power interruptibility for each customer (($\lambda_{j,t}$) are, and WT and PV output power adopted from [26]. The same two cases for MG test system 1 are employed for test system 2. Figure 6 shows the initial load and load after applying the different techniques of DRP, IDR and HDDR; It can be noted that in the case of using HDDR, the total peak hours(more than the average) load is much lower than IDR. The total initial peak hours' load is 23740 MWh; Using IDR program, around 1364.09 MWh load is reduced in peak hours and 1310.10 MWh in off-peak hours. For HDDR, the customers reduce their load consumption by 1819 MWh in peak periods with a higher reduction of around 450 MWh compared to the IDR program. So the MG reliability is enhanced due to this higher curtailment at peak hours.

For this test system, the optimal scheduling of the ten CDEs and the transaction power (P_{g_t}) are shown in Figure 7. Applying the HDDR program to test system 2, a detailed customer load reduction and incentive are indicated in Figure 8. Also, the cost breakdown comparison using the different techniques is detailed in Table 4 the results from this table indicate that the total cost achieved using POA is lower than PSO and slightly lower than the INFO technique. Also, Table 5 shows a comparison between the different techniques in terms of PRP; POA technique achieved the highest peak reduction percentage in the two studied DRP techniques, IDR and the proposed HDDR techniques, with 5.74% reduction in IDR and 7.66% in HDDR. Also, in this MG test system, the MGO benefit is the highest when POA is applied to solve the EM problem (Table 5).

From the results of the two test systems it can be noticed that using the proposed HDDR with POA optimization technique indicate that a greater reduction in customer consumption is achieved in the peak period, which helps maintain reliability.

7. Conclusion

This paper proposed a new application of a newly developed optimization algorithm, namely POA, to solve multi-objective optimization EM for Microgrid, considering a hybrid demand response program. The main objective of the EM problem is to reduce the overall operating cost, including the generation cost and transaction cost, while maximizing the MGO benefit. The HDDR technique is proposed to ensure MG reliability at peak hours. The proposed HDDR was developed as a combination of IDR and peak-based variable prices IDR (PIDR) programs to encourage customers to reduce their consumption during peak hours (above average load). HDDR is a dynamic DR program considering the load demand profile, and it does not use fixed hours as peak hours. The PIDR applied during peak periods was regarded as a function of peak intensity. PRP is employed to assess the superiority of the proposed HDDR with POA to reduce the peak load and maintain the reliability of the MG. In particular, the performance of the proposed technique was assessed by implementing two different MG test systems (systems 1 and 2). Comparative results of POA with well-known and newly-developed algorithms demonstrated that employing POA technique help achieved the lowest operating cost in the two test system for the two cases (IDR and HDDR). Also, the proposed method HDDR with POA achieved superior peak reduction outcomes for the total MG. According to POA's simulation results, using the HDDR reduce the peak load by 14.6% for the MG test system 1 and 7.6% for test system 2; in comparison to only 8.9% and 5.74% reduction by implementing CIDR. Furthermore, using the POA technique has achieved higher MG operator benefit with 50$ and 30$ in test system 1 and 3000$ and 2025$ for test system 2 using CIDR and the proposed HDDR respectively.

The proposed method can be extended to the probabilistic determination and to take into account uncertainties in demand, renewable energy generation and how it will affect the operation of the EM in MG.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that has been used is confidential.

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References

[1] J. Keirstead, M. Jennings, A. Sivakumar, A review of urban energy system models: Approaches, challenges and opportunities, Renewable and Sustainable Energy Reviews 16 (2012) 3847–3866, 2012/08/01.
[2] J. Wu, J. Yan, H. Jia, N. Hatziargyriou, N. Djilali, H. Sun, Integrated Energy Systems, Applied Energy 167 (2016) 155–157, 2016/04/01.
[3] N. Alamir, M.A. Ismeil, M. Orabi, New MPPT technique using phase-shift modulation for LLC resonant micro-inverter, in: 2017 Nineteenth International Middle East Power Systems Conference (MEPCON, 2017, pp. 1465–1470.
[4] R.H. Lasseter, "MicroGrids", in 2002 IEEE Power Engineering Society Winter Meeting. Conference Proceedings (Cat. No.02CH37309), 2002, pp. 305-308 vol.1.
[5] R. Alasseri, A. Tripathi, T. Joji Rao, K.J. Sreekanth, A review on implementation strategies for demand side management (DSM) in Kuwait through incentive-based demand response programs, Renewable and Sustainable Energy Reviews 77 (2017) 617–635, 2017/09/01.
[6] S.S. Reka and V. Ramesh, "Demand response scheme with electricity market prices for residential sector using stochastic dynamic optimization", in 2016 Biennial International Conference on Power and Energy Systems: Towards Sustainable Energy (PESTSE), 2016, pp. 1-6.
[7] P. Palensky, D. Dietrich, Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads, IEEE Transactions on Industrial Informatics 7 (2011) 381–388.
[8] A. Kamal, S.G. Al-Ghamdi, M. Koc, Revaluing the costs and benefits of energy efficiency: A systematic review, Energy Research & Social Science 54 (2019) 68–84, 2019/08/01.
[9] A.R. Jordehi, Optimisation of demand response in electric power systems, a review, Renewable and Sustainable Energy Reviews 103 (2019) 308–319, 2019/04/01.
[10] A.T.D. Perera, V.M. Nik, D. Mauree, J.-L. Scartezzini, Electrical hubs: An effective way to integrate non-dispatchable renewable energy sources with minimum impact to the grid, Applied Energy 190 (2017) 232–248, 2017/03/15.
[11] Z. Wang, B. Chen, J. Wang, J. kim, Decentralized Energy Management System for Networked Microgrids in Grid-Connected and Islanded Modes, IEEE Transactions on Smart Grid 7 (2016) 1097–1105.
[12] N. Nikmehr, S. Najafi-Ravadanegh, Optimal operation of distributed generations in micro-grids under uncertainties in load and renewable power generation using heuristic algorithm, IET Renewable Power Generation 9 (2015) 982–990.
[13] T. Chen, Y. Cao, X. Qing, J. Zhang, Y. Sun, G.A.J. Amaratunga, Multi-energy microgrid robust energy management with a novel decision-making strategy, Energy 239 (2022), 121840, 2022/01/15.
[14] A.L. Bukar, C.W. Tan, D.M. Said, A.M. Dobi, R. Ayop, A. Alsharif, Energy management strategy and capacity planning of an autonomous microgrid: Performance comparison of metaheuristic optimization searching techniques, Renewable Energy Focus 40 (2022) 48–66, 2022/03/01.
[15] M. Tostado-Véliz, S. Kamel, H.M. Hasanien, R.A. Turky, F. Jurado, Uncertainty-aware day-ahead scheduling of microgrids considering response fatigue: An IGDT approach, Applied Energy 310 (2022), 118611, 2022/03/15.
[16] P. Harsh, D. Das, Energy management in microgrid using incentive-based demand response and reconfigured network considering uncertainties in renewable energy sources, Sustainable Energy Technologies and Assessments 46 (2021), 101225, 2021/08/01.
[17] G. Aghajani, N. Ghadimi, Multi-objective energy management in a micro-grid, Energy Reports 4 (2018) 218–225, 2018/11/01.
[18] F.C. Robert, G.S. Sisodia, S. Gopalan, A critical review on the utilization of storage and demand response for the implementation of renewable energy microgrids, Sustainable Cities and Society 40 (2018) 735–745, 2018/07/01.
[19] A. Parisio, E. Rikos, L. Glielmo, A Model Predictive Control Approach to Microgrid Operation Optimization, IEEE Transactions on Control Systems Technology 22 (2014) 1813–1827.
[20] M.M. Gamil, T. Senjyu, H. Takahashi, A.M. Hemeida, N. Krishna, M.E. Lotfy, Optimal multi-objective sizing of a residential microgrid in Egypt with different ToU demand response percentages, Sustainable Cities and Society 75 (2021), 103293, 2021/12/01.
[21] M. Khosravi, H. Azarinfar, S. Ashkan Nejati, Microgrids energy management in automated distribution networks by considering consumers' comfort index, International Journal of Electrical Power & Energy Systems 139 (2022), 108013, 2022/07/01.
[22] H. Hua, Z. Qin, N. Dong, Y. Qin, M. Ye, Z. Wang, et al., Data-Driven Dynamical Control for Bottom-up Energy Internet System, IEEE Transactions on Sustainable Energy 13 (2022) 315–327.
[23] A. Arif, F. Javed, N. Arshad, Integrating renewables economic dispatch with demand side management in micro-grids: a genetic algorithm-based approach, Energy Efficiency 7 (2014) 271–284, 2014/04/01.
[24] A.-D. Nguyen, V.-H. Bui, A. Hussain, D.-H. Nguyen, H.-M. Kim, Impact of Demand Response Programs on Optimal Operation of Multi-Microgrid System, Energies 11 (2018) 1452.
[25] S. Fan, Q. Ai, L. Piao, Hierarchical Energy Management of Microgrids including Storage and Demand Response, Energies 11 (2018) 1111.
[26] N.I. Nwulu, X. Xia, Optimal dispatch for a microgrid incorporating renewables and demand response, Renewable Energy 101 (2017) 16–28, 2017/02/01.
[27] M.A. Shehzad Hassan, M. Chen, H. Lin, M.H. Ahmed, M.Z. Khan, G.R. Chughtai, Optimization modeling for dynamic price based demand response in microgrids, Journal of Cleaner Production 222 (2019) 231–241, 2019/06/10.

[28] V.S. Tabar, S. Ghassemzadeh, S. Tohidi, Energy management in hybrid microgrid with considering multiple power market and real time demand response, Energy 174 (2019) 10–23, 2019/05/01.

[29] Y. Sasaki, M. Ueoka, Y. Uesugi, N. Yorino, Y. Zoka, A. Bedawy, et al., A Robust Economic Load Dispatch in Community Microgrid Considering Incentive-based Demand Response, IFAC-PapersOnLine 55 (2022) 389–394, 2022/01/01.

[30] H.J. Kim, M.K. Kim, J.W. Lee, A two-stage stochastic p-robust optimal energy trading management in microgrid operation considering uncertainty with hybrid demand response, International Journal of Electrical Power & Energy Systems 124 (2021), 106422, 2021/01/01.

[31] H.-J. Kim, M.-K. Kim, Multi-Objective Based Optimal Energy Management of Grid-Connected Microgrid Considering Advanced Demand Response, Energies 12 (2019) 4142.

[32] M.D. Pavel Trojovský, Pelican Optimization Algorithm: A Novel Nature-Inspired Algorithm for Engineering Applications, Sensors (Basel, Switzerland) 22 (3) (2022) 855.

[33] D.H. Wolpert, William G. Macready, No free lunch theorems for optimization, IEEE transactions on evolutionary computation 1 (1997) 67–82, vol. 1, pp.

[34] P. Trojovský, M. Dehghani, Pelican Optimization Algorithm: A Novel Nature-Inspired Algorithm for Engineering Applications, Sensors (Basel, Switzerland) 22 (3) (2022) 855, https://doi.org/10.3390/s22030855.

[35] H. Tazvinga, B. Zhu, X. Xia, Energy dispatch strategy for a photovoltaic–wind–diesel–battery hybrid power system, Solar Energy 108 (2014) 412–420, 2014/10/01.

[36] D. Villanueva, J.L. Pazos, A. Feijoo, Probabilistic Load Flow Including Wind Power Generation, IEEE Transactions on Power Systems 26 (2011) 1659–1667.

[37] H. Tazvinga, X. Xia, J. Zhang, Minimum cost solution of photovoltaic–diesel–battery hybrid power systems for remote consumers, Solar Energy 96 (2013) 292–299, 2013/10/01.

[38] M. Fahrioglu, F.L. Alvarado, Designing incentive compatible contracts for effective demand management, IEEE Transactions on Power Systems 15 (2000) 1255–1260.

[39] N.I. Nwulu, M. Fahrioglu, A soft computing approach to projecting locational marginal price, Neural Computing and Applications 22 (2013) 1115–1124, 2013/05/01.

[40] D. Gotham, K. Muthuraman, P. Preckel, R. Rardin, S. Ruangpattana, A load factor based mean–variance analysis for fuel diversification, Energy Economics 31 (2009) 249–256, 2009/03/01.

[41] A. Raja and A.P. Srivastava, Power plant engineering: New Age International, 2006.

[42] J. Shen, C. Jiang, Y. Liu, J. Qian, A microgrid energy management system with demand response for providing grid peak shaving, Electric Power Components and Systems 44 (2016) 843–852.

[43] I. Boussaïd, J. Lepagnot, P. Siarry, A survey on optimization metaheuristics, Information sciences 237 (2013) 82–117.

[44] A. Darwish, Bio-inspired computing: Algorithms review, deep analysis, and the scope of applications, Future Computing and Informatics Journal 3 (2018) 231–246, 2018/12/01.

[45] A.A. Moghaddam, A. Seifi, T. Niknam, M.R. Alizadeh Pahlavani, Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source, Energy 36 (2011) 6490–6507, 2011/11/01.

[46] I. Ahmadianfar, A.A. Heidari, S. Noshadian, H. Chen, A.H. Gandomi, INFO: An efficient optimization algorithm based on weighted mean of vectors, Expert Systems with Applications 195 (2022), 116516, 2022/06/01.