Abir Hasnaoui[1], Abdelhafid Omari[2], Zin-eddine Azzouz[2]

Departement of Electrotechnics (1), Departement of Automatic (2), Faculty of Electrical Engineering, University of Science and Technology of Oran "Mohamed Boudiaf", Oran,Algeria.

doi:10.15199/48.2023.06.49

Coot Algorithm for Optimization and Management of Residential Power Demand

Abstract*. One of the major issues that investigators are working on is the rise in global electricity consumption. The main objective of this work is minimizing the total electricity cost of a residential house. In this current research a new metaheuristic algorithm that is inspired by the Coot swarm's behavior is applied. In addition to that, a comparison algorithm analysis is conducted using various metaheuristic methods. The results showed that employing the Coot optimization approach led to the lowest reduction in overall electricity daily cost.*

Streszczenie. *Jednym z głównych problemów, nad którymi pracują śledczy, jest wzrost globalnego zużycia energii elektrycznej. Głównym celem pracy jest minimalizacja całkowitego kosztu energii elektrycznej domu mieszkalnego. W obecnych badaniach zastosowano nowy algorytm metaheurystyczny, zainspirowany zachowaniem roju Łysek. Ponadto przeprowadzana jest analiza algorytmu porównawczego z wykorzystaniem różnych metod metaheurystycznych. Wyniki pokazały, że zastosowanie podejścia optymalizacyjnego Coota doprowadziło do najmniejszej redukcji całkowitego dziennego kosztu energii elektrycznej. (****Algorytm Coota do optymalizacji i zarządzania zapotrzebowaniem na energię w budynkach mieszkalnych****)*

Keywords: Minimizing the total electricity daily cost, Renewable Energy Sources, Coot Optimization Algorithm, Metaheuristic Algorithms.
Słowa kluczowe: Minimalizacja całkowitego dziennego kosztu energii elektrycznej, Odnawialne Źródła Energii, Algorytm Optymalizacji Coota, Algorytmy Metaheurystyczne.

Introduction

Incorporation of renewable energy sources is presently playing a crucial role in meeting the demands of rising power consumption while reducing environmental pollution and that can decrease reliance on nonrenewable energy sources like fossil fuels. Literature shows that progressively replacing nonrenewable energy sources with renewable energy sources such as solar energy, bioenergy, wind, hydropower, ocean energy, and geothermal energy will assist the world to reach the concept of sustainability [1].

According to the International Renewable Energy Agency (IRENA), several regions could significantly raise the overall proportion of renewable from about 18% of total primary energy supply to about two-thirds in 2050 [2].

Most significantly less expensive renewable power sources used are solar and wind power. Nevertheless, depending on weather unpredictability, the electricity delivered by these two energy sources is intermittent and volatile [3].

Since the solar and wind systems are insecure, intermittent, and expensive, the nonrenewable energy sources and energy storage systems have been included to assure a reliable and continuous electricity supply. When renewable energy sources are combined with additional energy sources, the system is referred to as a hybrid renewable energy system. There are two types of hybrid renewable energy systems: on grid which is connected to the main grid and off grid which is the isolated mode [4].

Otherwise, sundry optimization methods have been used by researchers. Thereby, in [5] P.Roy et al. used a particle swarm optimization and a curve fitting technique to get the best value of the low pass filter time constant of microgrids consisting of a wind, solar, battery and a supercapacitor hybrid energy storage subsystem, and minimizing the energy storage cost by utilizing a various control strategies. J.Martinez-Rico et al. [6] presented a nonlinear multi objective cost problem, where they used the particle swarm optimization method to minimize the loss of battery value and maximize the net profitability of the hybrid renewable power system. To reduce the carbon emission and the total cost of a hybrid renewable energy system consisting of a micro-gas turbine, a wind turbine, a solar panel and batteries, a global dynamic harmony search algorithm have been developed by S.Saib et al. [7] and compared with other metaheuristic methods as harmony search algorithm, improved harmony algorithm, particle swarm optimization and bat algorithm. In [8] J.Pahasa et al. presented an optimization method to produce the lowest possible coil inductance of a superconducting magnetic energy storage that ensures the stocked power firstly and to keep the state of charge at the appropriate scale secondly. Particle swarm optimization algorithm developed by L.Wang et al.[9] to treat hybrid generation system design cost issue by taking into consideration other objectives such as pollutant emissions and reliability too. I.Çetinbaş et al. [10] presented a new hybrid metaheuristic algorithm: the hybrid Harris hawks optimizer-arithmetic algorithm to handle the problem of sizing of microgrids. In [11] M .B.Danoune et al. a whale optimization algorithm was proposed and employed to determine the optimal characteristics of various proton exchange membrane fuel cells and compared the obtained results with those found by applying other metaheuristic optimization methods. A sailfish optimization algorithm was created by A.Xavier et al. [12] in order to increase overall deployment cost and quality of service efficiency depending on client requirements. S .J.Lee et al. [13] presented a strategy for optimizing power costs by mixing genetic algorithm and dynamic programming to tackle an Energy storage system scheduling issue with and without requirement load. In [14] L.Rao e al. proposed an optimization method to reduce the total power cost of distributed network information institutes by ensuring service quality in response to the region and temporal variety of power prices. Two methods: non-dominated sorted genetic algorithm and nonlinear programming were proposed and compared by A.Houbbadi et al. [15] for the purpose of reducing either power costs and battery life of the electric bus fleet. Z.Qu et al. [16] suggested a new approach: a continuous search multi-objective particle swarm algorithm to reduce the cost of electricity of the home appliance cointegration and domestic energy planning with concentrate to develop the user comfort. In [17] C.Paul et al. created a novel technique where they combined the chaotic nature with whale optimization algorithm to increase the issue's convergence speed .The chaotic base whale optimization algorithm developed to evaluate both heat, power cost dispatch and to reduce both fuel prices and emissions. To minimize the carbon emission of power grid with aluminum plants, a coot algorithm which is a new metaheuristic optimization method, applied by L.Qin et al. [18]. L.C.Kien et al. [19] applied three metaheuristic methods: coot optimization algorithm, transient search algorithm and crystal structure algorithm to decrease photovoltaic generator active power loss in distribution networks while accounting for variations in load and solar radiation.

Regarding the aforementioned literature review, it is clear that significant attempts have been made by employing different optimization strategies to address various challenges. Nevertheless, because the metaheuristic optimization domain is continually expanding over time, there are some possibilities to try novel techniques. Furthermore, although aside from the interesting solutions obtained, one strategy may be beneficial when dealing with one set of issues but may not be successful in tackling other types of issues, therefore it is generally advisable to test out various or novel strategies.

The main objective of this paper is to reduce the total electricity cost of a residential system consisting of two renewable energy sources (which are photovoltaic and wind turbine) and a battery storage system in order to fully meet the load demand and decrease the energy consumed from the grid. This hybrid system is connected to the main grid with a bidirectional connection. Therefore, the coot algorithm is the proposed optimization method to handle this issue. Two case studies are used to evaluate the effectiveness of the coot method. For such a proper comparison, the suggested technique's performance was evaluated versus three different metaheuristic algorithms. The following points highlight the important contributions and notable differences between this study and other research:

- A residential power system model has been developed to minimize the total electricity daily cost.
- To discover the optimal results of the hybrid system, a simple and efficient random search technique is suggested: coot optimization algorithm, as opposed to the algorithms used in previous research.
- The coot algorithm was developed to find the best optimum results of the main objective in this paper. The strategy provides the best optimal solution, the most stable ability as well as the best convergence.
- Contrary to earlier study by L.Qin et al.[18], which utilized the same approach as this research to minimize the carbon emission of the power grid, the reduction of total electricity cost of the proposed model using coot algorithm is explored in depth in this research.

The rest of this paper is organized as follows. The proposed residential energy system model is presented in section 2. The mathematical model of the hybrid system used in this paper and the various metaheuristic optimization algorithms are described in section 3 and section 4 respectively. Simulation results are presented and discussed in section 5. Finally, section 6 concludes the paper.

Residential Configuration and Description

In this paper, a coot optimization algorithm is applied to reduce the total electricity cost in a residential house connected to the main grid by a bidirectional connection. The hybrid system (Fig.1) based on renewable energy sources: photovoltaic and wind turbine, and a power storage system.

The transfer of power between the main grid and the residential house is bilateral in the sense that when renewable power generation is inadequate, the load utilizes power from the main grid or from the power storage system, based on the state of charge and the storage system power. Additionally, surplus power created by renewable power sources is transferred to the battery or sold to the main grid.

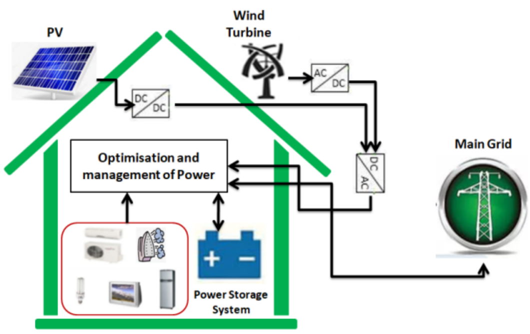

Fig.1. Grid-connected residential power system

The hybrid system input data employed in this work was utilized in research [20]. Fig. 2 depicts the daily expected data power load requirement, solar supplied power, and wind turbine supplied power with a sample period of one hour. Fig. 3 shows the cost of grid-supplied or purchased power. The 3.5kW photovoltaic system has a total area of 25m2 and an efficiency of 18.6%. The 2.4kW wind micro turbine has a nominal speed of 14m/s, a cut-out speed of 25m/s, and a rated output of 2.1kW.

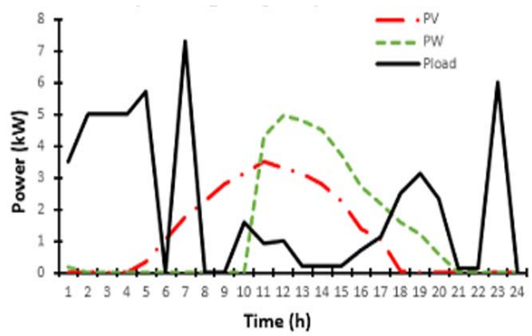

Fig.2. Load demand, photovoltaic and wind turbine power in the 24h

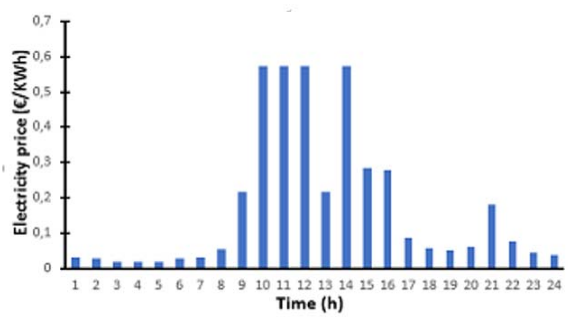

Fig.3. Electricity price

Mathematical Model

The optimization challenge necessitates the establishment of the power mathematical model of the analyzed hybrid energy system, shown in Fig. 1. In this paper the optimization problem is linear which includes linear constraints.

1. Power Balance Model

In a hybrid power system, the entire load's electricity needs should be met at all times (the total power requirement matches the total power supply). As a result, the utilization of power provided by photovoltaic system and wind turbine system to supply loads is overflowing, and when demand is met, the excess is charged in batteries or sold to the main grid. Otherwise, the power deficiency will be compensated by power from batteries or the main grid. The Equation (1) represents the power balance in each period (t).

$$P_{grid}(t) - P_{bat}(t) + P_{PV}(t) + P_{wind}(t) = P_{load}(t) \quad (1)$$

where: P_{grid} – the net grid power in [kW], P_{bat} – the battery charge and discharge power in [kW], P_{PV} – the photovoltaic power [kW], P_{wind} – the wind turbine power, P_{load} – power demand of residential [kW].

2. Grid and Power Storage System Constraints

The problem function is dependent on constraints to create a viable optimal solution, which are described as equalities and inequalities equations that put a boundary on the issue's parameters. The power imported from/to the grid, the charging/discharging power of battery, the photovoltaic power and the wind turbine power are represented by the following inequality equations:

$$P_{sell}^{\max} \le P_{grid}(t) \le P_{grid}^{\max} \quad (2)$$

$$P_{bat}^{dis} \le P_{bat}(t) \le P_{bat}^{ch} \quad (3)$$

$$P_{PV}(t) \ge 0 \quad (4)$$

$$P_{wind}(t) \ge 0 \quad (5)$$

where: $P_{grid}^{\max}$ – the maximum power consumed from grid [kW], $P_{sell}^{\max}$ – the maximum power injected to the grid [kW], P_{bat}^{ch} – the maximum power charged in battery [kW], P_{bat}^{dis} – the maximum power discharge from battery [kW].

3. Problem Formulation

The aim of this paper is to optimize the power flux in the hybrid power system illustrated in Fig.1 by reducing the power consumption from the main grid and minimizing the cost of the electric load bill. The total electricity cost function is defined as follows:

$$\min f = \sum_{t=1}^{24} \begin{bmatrix} C_{grid}(t) * P_{grid}(t) * dt + C_{bat}(t) * P_{bat}(t) * dt + \\ C_{PV} * P_{PV}(t) * dt + C_{wind} * P_{wind}(t) * dt \end{bmatrix} \quad (6)$$

where: C_{grid} – the Electricity cost [€/kWh], P_{grid} – the bought and sold power from the main grid [kW], C_{bat} – the maintenance price of battery storage system [€/kWh], P_{bat} – the charging and discharging power of battery [kW], C_{wind} and C_{PV} – the maintenance and production cost of wind turbine and photovoltaic power respectively.

Optimization Algorithm

Many innovative algorithms have lately been developed in order to identify the optimum answer for challenging engineering issues. These algorithms can explore volatile and multidimensional problem fields for optimum solutions instantaneously.

A new metaheuristic method: Coot optimization algorithm, applied in this paper to minimize the total electricity daily cost of a residential house. To validate the accuracy, reliability and the optimal results of the method a comparison study of the total electricity cost convergence is conducted using various metaheuristic algorithms as the particle swarm optimization, whale optimization algorithm and sailfish optimization algorithm.

1. Coot Optimization Algorithm

I.Naruei et al. [21] suggested a novel metaheuristic technique in 2021 that inspired from the behaviors and movements of the Coot swarm. Coots travel at an angle to their own velocity. Additionally, the behavior of a swarm of coots on water involves three movements: a chaotic movement of activity, a coordinated movement, and a chain movement on the water's surface, with each coot moving behind its lead coot. It has been discovered that coots have four distinct movements on the watery area, which may be defined in detail below.

1.1 Random Movement to This Side and That Side

The coot movement examines several distinct areas of the search field, because of that the equation (7) is employed to maintain the coot's position to avoid the answer from being trapped in a locally ideal place.

$$Cootpos(i) = Cootpos(i) + A * R2 * (Q - Cootpos(i)) \quad (7)$$

where: *Cootpos(i)* – the coot position, *R2* – a random variable in the interval [0, 1], *A and Q* – counted by equation [8] and [9] respectively.

$$A = 1 - \frac{iter}{Max\_iter} \quad (8)$$

$$Q = rand(1, d) * (ub - lb) + lb \quad (9)$$

where: *iter* – current iteration, *Max_iter* – the maximum iteration, *d* – the set of decision variables, *ub and lb* – the upper and lower bound of the search space respectively.

1.2 Chain Movement

One of the way to execute a chain movement is by calculate the average between two respectively coot position [18], which is defined by the equation (10):

$$Cootpos(i) = \frac{(Cootpos(i-1) + Cootpos(i)}{2} \quad (10)$$

1.3 Adjusting the Position Based on the Group Leaders

Typically, the group is directed by a few coots ahead of the group, and the remainder of the coots must change its posture and move toward the group's commanders. Depending on the average location, every coot would modify its position. To carry out this motion, we employ a method based on equation (11) to pick the leader.

$$K = 1 + (i \ MOD \ NL) \quad (11)$$

where: *K* – indicator value of the current leaders, *i* – indicator value of the current coot, *NL* – the number of leaders.

The i^{th} coot should set its position based on the leader's k which is defined by th equation a (12).

$$Cootpos(i) = Leaderpos(K) + 2 * R1 * \cos(2 * R * \pi) * (Leaderpos(k) - Cootpos(i)) \quad (12)$$

where: *Cootpos(i)* – the current position of coot, *R1* – a random value in the interval [0, 1], *R* – a random value in the interval [− 1, 1], *Leaderpos(k)* – selected leader position.

1.4 Leading the Group by the Leaders towards the Optimal Area (Leader Movement)

Leaders must adjust their position toward the target in order to drive the gathering toward a target (ideal zone). To modify the position of leaders, Equation (13) is suggested. This equation seeks better placements near the present optimum spot. Leaders must often shift away from their existing best position in order to discover good places. That equation is a fantastic approach to go nearer to and away from the ideal spot.

(13)
$$Leaderpos(i) = \begin{cases} B * R3 * \cos(2 * R * \pi) * (gBest - Leaderpos(i)) + gBest & R4 < 0.5 \\ B * R3 * \cos(2 * R * \pi) * (gBest - Leaderpos(i)) - gBest & R4 \geq 0.5 \end{cases}$$

where: *B* – calculated according to equation (14), *R3 and R4* – random number in the interval [0, 1], *gBest* – the best position ever found.

(14)
$$B = 2 - \frac{iter}{Max\_iter}$$

where: *iter* – current iteration, *Max_iter* – the maximum iteration.

2. *Whale Optimization Algorithm*

This method is a population-based, stochastic discovery strategy. Indeed, S.Mirjalili et al. [22] suggested it in 2016 to imitate the behavior of humpback whales. Because it is quick in discovering the global-optimum, simple to code, and needs limited critical factors, the approach has been effectively employed in various engineering situations. The optimization technique is divided into three major phases, which are explained below [22]:

2.1 Encircling the Prey

It is essential for anticipating the prey's possible location. Because hunters do not know where their meal is at the start, the best agent $\vec{X}^*$ in the swarm is chosen as the goal. Equation (15) determines the gap among agent and best agent. The leftover agent must now pursue the goal, as shown in Equation (16). It is important to mention here that $\vec{X}^*$ must be modified at each repetition if a greater option exists.

(15)
$$\vec{D} = \left| \vec{C} * \vec{X}^* - \vec{X}(i) \right|$$

(16)
$$\vec{X}(i+1) = \vec{X}^* - \vec{A} * \vec{D}$$

where: $\vec{D}$ – the distance vector between the best position and the agents. We can calculate the constant vectors $\vec{C}$ and $\vec{A}$ with (17) and (18).

(17)
$$\vec{C} = 2 * \vec{r}$$

(18)
$$\vec{A} = 2 * \vec{a} * \vec{r} - \vec{a}$$

where: $\vec{r}$ – a random value from [0,1], $\vec{a}$ – take a linear decreasing value from 2 to 0.

2.2 Bublle Net Attacking

It is a unique fishing strategy used by humpback whales. It was discovered that the searching method is carried out by the generation of unique bubbles. Equation (19) might be used to replicate this phenomenon.

(19
$$\vec{X}(i+1) \begin{cases} \vec{X}^* - \vec{A} * \vec{D} & if\ p \prec 0.5 \\ \vec{D}' * e^{b*l} * \cos(2 * \pi * l) + \vec{X}^* & if\ p \geq 0.5 \end{cases}$$

Where: *p* – a random variable from 0 to 1, *b* – equal to 1, *l* – a random value that lies in -1 ≤ *l* ≤ 1.

2.3 Seeking for the Prey

The whale optimization algorithm search technique requires all particles to participate to the search strategy. To ensure that a global search is done in all area, the particles are compelled to wander far away from the reference whale, as theoretically indicated in Equation (20) and (21).

(20)
$$\vec{D} = \left| \vec{C} * \vec{X}_{rand}(i) - \vec{X}(i) \right|$$

(21)
$$\vec{X}(i+1) = \vec{X}_{rand}(i) - \vec{A} * \vec{D}$$

where: $\vec{X}(i+1)$ – the position, which is randomly taken from the current particle.

3. *Particle Swarm Optimization*

J.Kennedy et al.[23] developed the PSO method, a meta-heuristic optimization approach, in 1995. It is a simple strategy that looks to be effective for improving a wide range of functions. Social optimization occurs in the context of everyday life. In addition to its connections with nature, particle swarm optimization has obvious connections with computational. Abstractly, it looks to be somewhere between genetic algorithms and evolutionary programming. It relies significantly on random mechanisms like evolutionary programming [23].

The Particle swarm optimization is a metaheuristic that is commonly used in many fields. It was created as a computational strategy focused on repetition to achieve the best possible outcome. It is based on the activity of the swarm's particles in a multivariate environment and is influenced by the social behavior of bird swarms. The particles are randomly adjusted in each iteration [24-25] by using the velocity and position equations.

The particles are given a random beginning place in the procedure. By using equations (22) and (23), the position and velocity of each swarm particle are changed at each repetition depending on the best present position:

(22)
$$V_i(k+1) = w * V_i(k) + c1 * r1 * (X_{i,best}(k) - X_i(k) + c2 * r2 * (X_{g,best}(k) - X_i(k))$$

(23)
$$X_i(k+1) = X_i(k) + V_i(k+1)$$

where: X_i – the particle position, $X_{i,best}$ – the best particle position in the current iteration , $X_{g,best}$ – the global best position of the particles which represents the optimal solution in the current iteration, V_i – the velocity, w is the inertia weight coefficient for particles, *c1* and *c2* – the personal and social acceleration coefficients, *r1* and *r2* – a random numbers from [0, 1].

4. *Sailfish Optimizer Algorithm*

It is a metaheuristic algorithm based on population investigated by S.Shadravan et al.[26] in 2019. It was influenced by a group of sailfish hunters. This strategy comprises two population tips: sailfish for intensifying the hunt around the greatest so far, and sardines for diversifying the hunt zone. The sailfish are supposed to be possible answers in this technique, and the issue parameters are the location of the sailfish in the search area. As a result, the population in the solution space is created at random. With their changeable location vectors, sailfish may hunt in one or multidimensional areas.

To illustrate the proposed technique, consider that sailfish locations are the variables of all answers, and that the ith member at the kth search agent has a current location SFi,k in a d-dimensional search area. All sailfish positions are recorded to the SF matrix, and the following matrix displays the global optimum for all results:

(24)
$$SF_{Fitness} = \begin{bmatrix} f(SF_{1,1}\ SF_{1,2}..........SF_{1,d}) \\ f(SF_{2,1}\ SF_{2,2}..........SF_{2,d}) \\ \vdots \quad \vdots \quad \vdots \\ f(SF_{m,1}\ SF_{m,2}.........SF_{m,d}) \end{bmatrix} = \begin{bmatrix} F_{SF_1} \\ F_{SF_2} \\ \vdots \\ F_{SF_m} \end{bmatrix}$$

where: $SF_{i,j}$ – shows the value of the *jth* dimension of the ith sailfish, *f* – calculates the cost function and will be saved in the matrix $SF_{Fitness}$, *m* – indicates the number of sailfish.

The algorithm also includes a considerable number of sardines. The fleet of sardines is supposed to be swimming in the search area, and their locations will be recorded to the matrix S so that their optimum values may be used as follows:

$$S_{Fitness} = \begin{bmatrix} f(S_{1,1}\ S_{1,2}..........S_{1,d}) \\ f(S_{2,1}\ S_{2,2}.........S_{2,d}) \\ \vdots \quad \vdots \quad \vdots \\ f(S_{n,1}\ S_{n,2}.........S_{n,d}) \end{bmatrix} = \begin{bmatrix} F_{S_1} \\ F_{S_2} \\ \vdots \\ F_{Sn} \end{bmatrix} \tag{25}$$

where: $S_{i,j}$ – indicates the value of the *jth* dimension of the *ith* sardine, *f* – calculates the cost function of each sardine and saves in the matrix $S_{Fitness}$, *n* – the number of sardines.

Furthermore, the location of the sailfish will be adjusted during the optimization process. At the i_{th} iteration, the new location of sailfish $X^{i}_{new_{SF}}$ is modified as follows:

$$X^{i}_{new\ SF} = X^{i}_{elite\ SF} - \lambda_i * (rand\ \ (0,1) * \left(\frac{X^{i}_{elite\ SF} + X^{i}_{injured\ \ S}}{2}\right) - X^{i}_{old\ SF}) \tag{26}$$

where: $X^{i}_{elite_{SF}}$ and $X^{i}_{injured_S}$ – the best positions of sailfish and sardines respectively, $X^{i}_{old_{SF}}$ – determines the current position of sailfish, *rand(0,1)* – a random number between 0 and 1, λ_i – generated as follows:

$$\lambda_i = 2 * rand(0,1) * PD - PD \tag{27}$$

Because the quantity of prey decreases while team fishing, the PD parameter is important for adjusting the location of sailfish around the prey group and indicates the amount of prey at each iteration as follows:

$$PD = 1 - \left(\frac{N_{SF}}{N_{SF} + N_S}\right) \tag{28}$$

where: N_{SF} and N_S – the number of sailfish and sardines at each iteration, respectively.

The suggested alternate assault and surrounding technique form a circle-shaped area around the answers for predators pursuing prey from various directions. Furthermore, it is possible to simulate updating the location of sardines at the ith iteration as follows:

$$X^{i}_{new_s} = r * (X^{i}_{elite_{SF}} - X^{i}_{old_S} + AP) \tag{29}$$

where: *r* – a random number between [0,1], $X^{i}_{elite_{SF}}$ – the perfect location of sailfish made so far, $X^{i}_{old_S}$ – current location of sardines, and the quantity of sailfish attacking force is saved in the *AP* factor produced as follows:

$$AP = A * (1 - (2 * Itr * \varepsilon)) \tag{30}$$

where: A and ε – coefficients for decreasing the value of power attack linearly from A to 0. By using the AP parameter, the number of sardines that adjust their location *α* and the number of variables of issue *β* can be calculated as follows:

$$\alpha = N_S * AP \tag{31}$$

$$\beta = d_i * AP \tag{32}$$

where: N_s – indicates the number of sardines , d_i – the number of variables at the ith iteration.

Last, to maximize the likelihood of catching the new prey, the position of the sailfish replaces the most recently caught sardine. The following is the adaptable equation:

$$X^{i}_{SF} = X^{i}_{S} \qquad if\ f(S_i) \prec f(SF_i) \tag{33}$$

where: X^{i}_{SF} – the current location of sailfish, X^{i}_{S} – the current location of sardine in the i_{th} iteration.

Simulation Results and Discussion

Two different scenarios were built in this research utilizing data from the reference [20], to solve the optimization problem of lowering the total electricity cost of a residential home demand. The first scenario was by using two different numbers of iterations: 300 and 500 and the second one was by using two different numbers of particles: 10 and 30. As aforementioned, the proposed power management system was simulated using various metaheuristic optimization approaches: coot optimization algorithm, whale optimization algorithm, particle swarm optimization and sailfish optimizer algorithm.

The produced programs were run many times separately. As the needed response, the lowest of the potential answers was picked. The calculations were performed on a single laptop that was set up as follows: Windows 7 64-bit, Intel (R) Core(TM) i7-2670QM processor. RAM is 6.0 GB, and the processing speed is 2.20 GHz. The program utilized was MATLAB R2019a.

1. 300 Iterations

Throughout 300 iterations, the created codes were performed several times separately. As is shown in Fig. 4 and Fig. 5, where we compared the electricity total cost convergence results of codes simulation, using the various optimization methods suggested in this paper, the best reduced electricity daily total cost, by applying the two different numbers of particles was obtained by the coot optimization method.

Moreover, from the convergence curve (Fig. 4 and Fig. 5) it can be viewed that the whale optimization approach has converged rapidly compared with the other optimization methods used.

Furthermore, the lowest starting value from the first iteration (Fig. 5) was obtained by using the coot optimization algorithm.

The grid and storage system power results by using the coot optimization method are depicted in Fig. 6 and Fig. 7, where the positive power is the utilized power from the network and the negative power is the injected power into the network. The largest bought power from the grid was from the earliest hours of the day and at night, from 1a.m. to 7a.m. and at 7 p.m. ,8 p.m. and 11 p.m., when renewable energy sources were insufficient to fulfill household demand and the electric power tariff was at its lowest rate. Additionally, the most electricity was injected into the grid between 8 a.m. and 5 p.m., when we had the most power produced by renewable energy sources and the electric power price was at its greatest level, thereby lowering the cost.

The battery storage system mostly is charged at 6 a.m. and from 8 a.m. to 5 p.m. by surplus renewable energy sources and discharged from 1 a.m. to 5 a.m., at 7 a.m., 6 p.m. to 8 p.m. and at 11 p.m. to fulfill load requirements when the renewable energy sources power are insufficient.

1. 500 Iterations

In the second case, where the produced programs were executed numerous times individually throughout the course of 500 iterations, the coot acquired the best reduced electricity total cost; the results are illustrated in Fig. 8 and Fig. 9.

In addition, from the convergence results curve (Fig. 8 and Fig. 9) it can be viewed that the coot optimization approach has converged swiftly compared with the other optimization methods used and as well the lowest starting value from the first iteration was obtained by using the coot optimization algorithm too.

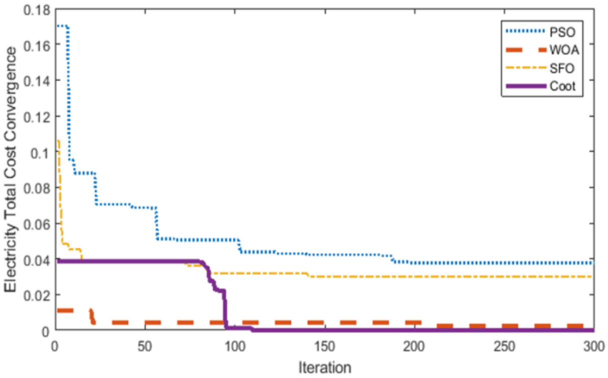

Fig.4. Electricity total cost convergence by using 300 iterations and 10 particles

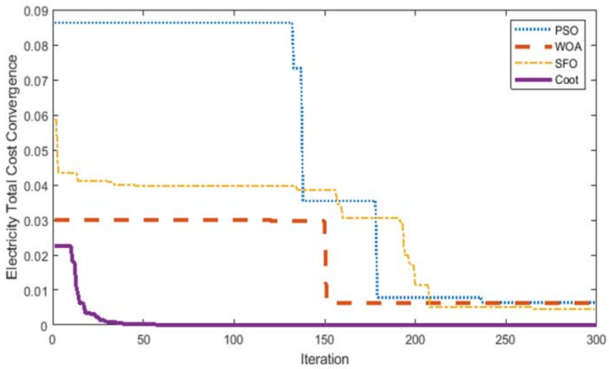

Fig.5. Electricity total cost convergence by using 300 iterations and 30 particles

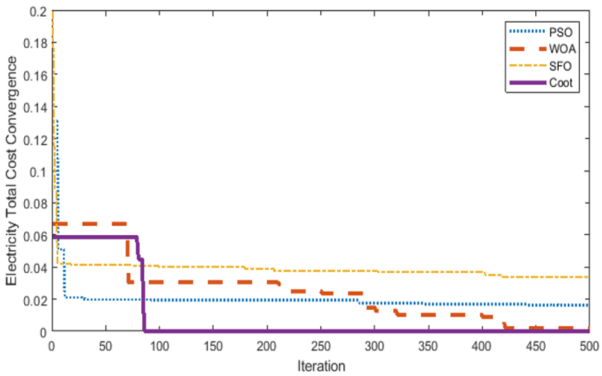

Fig.8. Electricity total cost convergence by using 500 iterations and 10 particles

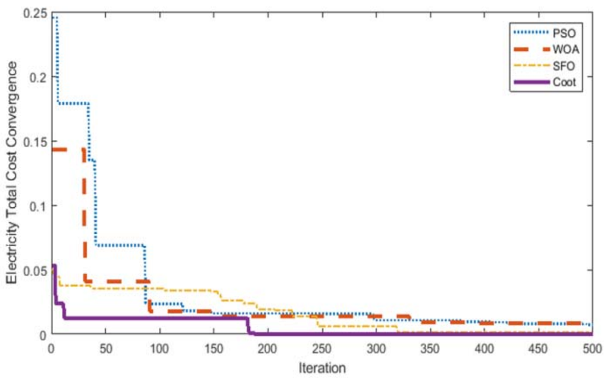

Fig.9. Electricity total cost convergence by using 500 iterations and 30

particles

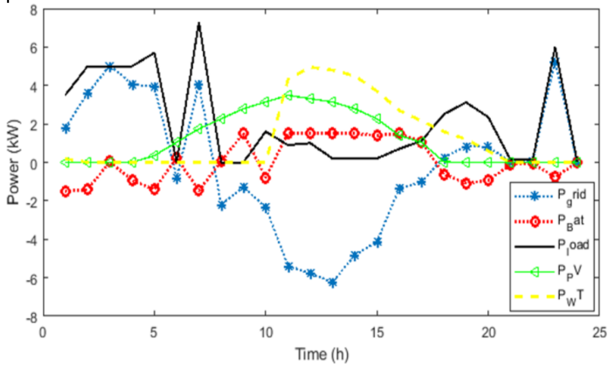

Fig.6. Grid and Battery Power by using 300 iterations and 10 particles

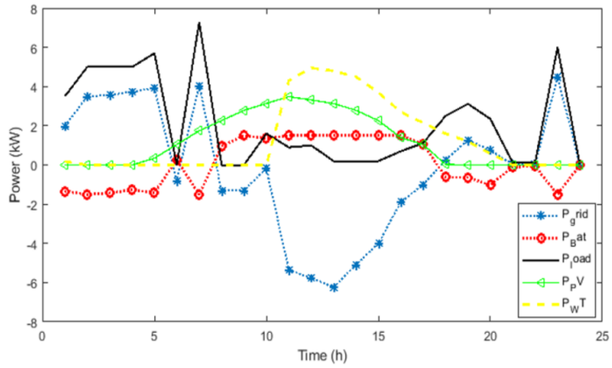

Fig.7. Grid and Battery Power by using 300 iterations and 30 particles

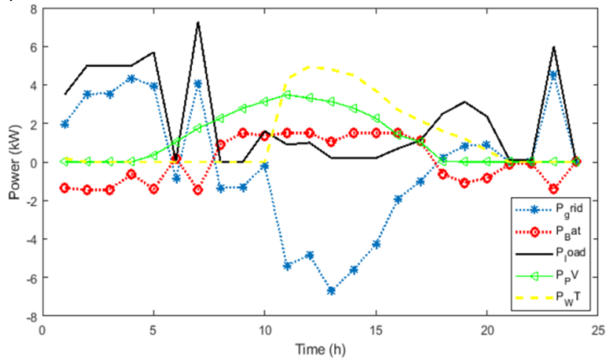

Fig.10. Grid and Battery Power by using 500 iterations and 10 particles

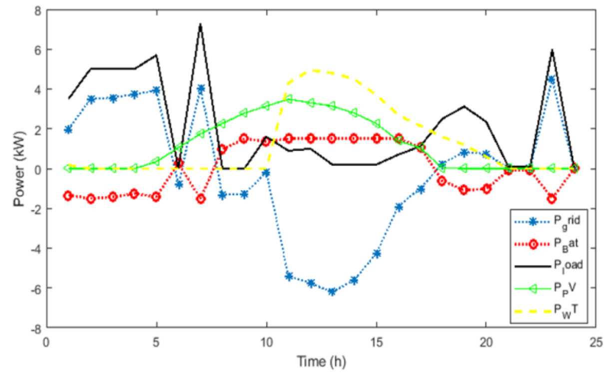

Fig.11. Grid and Battery Power by using 500 iterations and 30 particles

Fig. 10 and Fig. 11 represent the grid and storage system power, where the positive power is the consumed power from the main grid and the negative power is the injected power into the main grid. The most power obtained from the network was in the morning hours and late at evening, from 1 a.m. to 5 a.m., 6 p.m. to 8 p.m., and 11 p.m., when renewable energy sources were not enough to meet the home need and the electric power price was at its cheapest rates. Moreover, the most electricity was injected into the network at 6 a.m. and between 8 a.m. and 5 p.m., when we had the much more renewable energy produced and the electric power rate was at its highest, thereby lowering the cost.

The battery storage system is mostly filled at 6 a.m. from 8 a.m. to 5 p.m. by excess renewable energy sources and unloaded at 1 a.m. to 5 a.m., 7 a.m., 6 p.m. to 8 p.m., and 11 p.m. to meet load needs when renewable energy sources power is insufficient.

Conclusion

The coot algorithm was suggested and used in this research to identify the lowest overall power cost in a residential home, comprising two renewable energy sources (photovoltaic and wind turbine) and a battery storage system connected to a central network. This link enables bidirectional power transmission from and to the central network. A thorough investigation was performed to establish the suggested method's stability, dependability, and robustness.

Various metaheuristic optimization methods were applied and the results were compared in this research: coot optimization algorithm, particle swarm optimization, sailfish optimization algorithm and whale optimization algorithm.

The coot technique has ranked first in the majority of cases by giving the lowest daily cost. In addition, the efficacy of the established model by coot was examined with different numbers of iterations.

Based on the simulation results, the proposed approach demonstrated its dependability and efficiency in achieving the lowest overall power cost when compared to other metaheuristic recommended algorithms.

***Authors**: PhD Student. Abir Hasnaoui, Electrotechnics department, E-mail: abir.hasnaoui@univ-usto.dz; Pr. Abdelhafid Omari, E-mail: abdelhafid.omari@gmail.com, Pr. Zin-eddine Azzouz, Email: zinazzouz@yahoo.fr, Automatic Departement, Faculty of Electrical Engineering, University of Science and Technology of Oran “Mohamed Boudiaf”, Oran,Algeria.*

REFERENCES

[1] P.A.Owusu and S.A.Sarkodie, « A review of renewable energy sources, sustainability issues and climate change mitigation », *Cogent Engineering*,(2016),1-14

[2] REmap team at IRENA’s Innovation and Technology Centre, « GLOBAL ENERGY TRANSFORMATION » , (2018)

[3] M.A.M.Mladjao, I.El Abbassi, M.El Ganaoui and M.Darcherif, “ Modelisation et optimisation de systemes multi sources/Multi charges pour la ville durable,” *Ecobat Sciences & Techniques*, (2014), 210-220

[4] M.Kharrich, S.Kamel, M.Abdeen, O.H.Mohammed ,M.Akherraz, T.Khurshaid and S.B.Rhee, « Developed Approach Based on Equilibrium Optimizer for Optimal Design of Hybrid PV /Wind/ Diesel/Battery Microgrid in Dakhla, Morocco »,*IEEE*,(2021)

[5] P.Roy, J.He and Y.Liao, « Cost Minimization of battery-Supercapacitor Hybrid Energy Storage for Hourly Dispatching Wind-Solar Hybrid Power System », *IEEE*, (2020) 210099-210115

[6] J.Martinez-Rico,E.Zulueta, I.Rouiz de Argandona, U.Fernandez-Gamiz and M.Armendia, « Multi-Objective Optimization of Production Scheduling Using Particle Swarm Optimization Algorithm for Hybrid Renewable Power Plants with Battery Energy Storage System », *Journal of modern power systems and clean energy*, (2021), 285-294

[7] S.Saib, A.Gherbi, R.Bayindir and A.Kaabeche, « Multi-Objective Optimization of a Hybrid renewable energy System with a Gas Micro-turbine and a Storage Battery », *arabian Journal for Science and Enegineering*, (2019)

[8] J.Pahasa and I.Ngamroo, « Tow-Stage Optimization based on SOC Control of SMES Installed in Hybrid Wind/PV System for Stabilizing Voltage and Power Fluctuations », *IEEE*,(2021)

[9] L.Wang and C.Singh , « Multicriteria Design of Hybrid Power Generation Systems Based on a Modified Particle Swarm optimization Algorithm »,*Transactions on Energy Conversion*, *IEEE*, (2009), 163-172

[10] I.Çetinbaş, B.Tamyürek and M.Demirtaş, « The Hybrid Harris Hawks Optimizer-Arthmetic Optimization Algorithm : A New Hybrid Algorithm for Sizing Optimization and Design of Microgrids », *IEEE*, (2022),19254-19283

[11] M.B.Danoune, A.Djafour, Y.Wang and A.Gougui, « The Whale Optimization Algorithm for efficient PEM fuel cells modeling », *Elsevier*, (2021)

[12] A.Xavier, S.S.Ajitha and Shalini N M, « Multi Objective Sailfish Optimization Algorithm for Balancing Tradeoff amongst Cost and QoS for Resource Allocation in Cloud Computing », *Journal of soft computing and engineering applications*, (2020), 8-18

[13] S.J.Lee and Y.Yoon, « Electricity Cost Optimization in Energy Storage Systems by Combining a Genetic Algorithm with Dynamic Programming », *Mathematics*, (2020), 1-20

[14] L.Rao, X.Liu, L.Xie and W.Liu, « Minimizing Electricity Cost : Optimization of Distributed Internet Data Centers in a Multi-Electricity-Market Environment », *IEEE*, (2010)

[15] A.Houbbadi, E.R.Iglesias, R.Trigui, S.Pelissier and T.Bouton, « Optimal Charging Strategy to Minimize Electricity Cost and Prolong Battery Life of Electric Bus Fleet », *IEEE*, (2020)

[16] Z.Qu, N.Qu, Y.Liu, X.Y.Qu, W.Wang, and J.Han, « Multi-Objective Optimization Model of Electricity Behavior Considering the Combination of Household Appliance Correlation and Comfort », *J Electr Eng Technol*, (2018), 1821-1830

[17] C.Paul P.K.Roy V. Mukherjee, « Chaotic whale optimization algorithm for optimal solution of combined heat and power economic dispatch problem incorporating wind », *Journal pre proof*, (2020)

[18] L.Qin, T.Xu , S.Li, Z.Chen, Q.Zhang, J.Tian and Y.Lin, « Coot Algorithm for Optimal Carbon-Energy Combined Flow of Power Grid With aluminum Plants », *Frontiers*, (2022)

[19] L.C.Kien, T.T.B.Nga, T.M.Phan and T.T.Nguyen, « Coot Optimization Algorithm for Optimal Placement of Photovoltaic Generators in Distribution Systems Considering Variation of Load and Solar Radiation », *Hindawi Mathematical Problems in Engineering*, (2022), 1-17

[20] F.Y.Melhem, O.Grunder, Z.Hammoudan and N.Moubayed, “Optimization and Energy Mangement in Smart Home Considering Photovoltaic, Wind, and Battery Storage System With Integration of Electric Vehicles”, Canadian journal of electrical and computer engineering, *IEEE,* (2017), 128-138

[21] I. Naruei and F.Keynia, « A new optimization method based on COOT bird natural life model », *Elsevier*, (2021)

[22] S.Mirjalili and A.Lewis, “The Whale Optimization Algorithm”, *Advances in engineering Software, Elsevier*, (2016), 51-67

[23] J.Kennedy and R.Eberhart “Particle Swarm Optimization”, International Conference on Neural Networks, *IEEE*, (1995), 1942–1948

[24] M.Kharrich, O.H.Mohammed and M.Akherraz, “Design of Hybrid Microgrid PV/Wind/Diesel/Battery System: Case Study for Rabat and Baghdad”, *EAI Endorsed Transactions on Energy Web*, (2020), 1-9

[25] A.Bouakkaz, S.Haddad and A.J.G.Mena, “Optimal Peak Power Shaving Through Household Appliance Scheduling in off-grid Renewable Energy System”, *EEEIC / I&CPS Europe, IEEE*, (2019)

[26] S.Shadravan, H.R.Naji and V.K.Bardsiri, “The Sailfish Optimizer: A novel nature-inspired metaheruristic algorithm for solving constrained engineering optimization problems”, *Engineering Applications of Artificial Intelligence*, *Elsevier*, (2019), 20-34