Energy Scheduling of Isolated Microgrid with Battery Degradation Cost using Hybrid Particle Swarm Optimization with Sine Cosine Acceleration Coefficients

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Abstract- The implementation of renewable generators together with a battery storage into an isolated Microgrid (MG) has become essential to minimise fuel utilization and contribute to maintain continuous supply of electricity. This paper studies the optimal set point of isolated MG units containing renewable generators, diesel generators and battery storage. The optimal energy dispatch of MG's units is determined to supply the required load demand for a 48h horizon time. As the battery device has an important contribution in the MG, this paper proposes to implement battery degradation cost in the optimization model in addition to the fuel cost function. For this purpose, the Rainflow algorithm is used to count charging-discharging cycles and quantify the battery degradation. In addition, a Hybrid Particle Swarm Optimization with Sine Cosine Acceleration Coefficients (H-PSO-SCAC) algorithm is used to solve the defined objective function for an optimal energy management system of the isolated MG. A Weight Factor (WF) is proposed in the objective function. For the simulation tests, different values of WF are considered. The impact of WF is analysed on the algorithm behaviour, on the status of the State Of Charge (SOC) of the battery and its influence on the optimized MG cost function. The results demonstrate that the selection of an appropriate value of WF allows to the H-PSO-SCAC algorithm to achieve the best solution. In addition, with WF equals to 0.5, the charge/discharge cycles are reduced and the battery SOC is more stable.

Keywords Microgrid; hybrid resources; battery degradation cost; weight factor; Rainflow algorithm; hybrid particle swarm optimization with sine cosine acceleration coefficients.

1. Introduction

A Microgrid (MG) is a distribution electrical network that facilitates the penetration of different local generation sources, with or without storage devices [1]. For reliability and economic purposes, a MG can include Renewable Energy Source (RES), conventional generators, storage devices and consumption loads. A MG can operate in both Grid-Connected (GC) mode or isolated mode. In GC mode, the MG is linked to the main grid through a point of common coupling, and an energy trading can be of benefit by exchanging energy with the grid as buyer or seller.

An Energy Management System (EMS) has been widely utilized for an optimal dispatch of MG units. The EMS strategies can optimize the dispatching of the power output of the MG generating units, satisfy the Load Demand (LD) in economic manner, and properly regulate the frequency and voltage of the MG systems. Boqtob et al. [2] can be useful as a state of the art of MG-EMS frameworks, depicting the different generation units and storage devices used in MG structure, the integration of combined heat and power systems and electric vehicles, and the main Objective Functions (OFs) and constraints which are modelled in MG-EMS as well as the used optimization techniques.

The most installed RES in MG is Photovoltaic (PV) power and wind power. However, due to the intermittent behaviour of renewable sources, it is preferable to be accompanied by appropriate storage units and optimally incorporated into MG system.

Given the attention to the optimal utilization of Battery Storage (BS) in MG, several studies have been investigated to find the optimal dispatch of MG generation and storage units. For this purpose, various advanced optimization techniques have been reported. A Mixed Integer Linear Programming (MILP) is used in [3] to solve the optimal scheduling of Wind Turbine (WT) in MG with PV, Diesel Generator (DG) and BS. The paper discussed the effect of WT scheduling on the battery capacity as well as renewable generation and cost reduction. A Genetic Algorithm (GA) combined with fuzzy inference systems is proposed in [4] to solve the EMS for GC-MG with Energy Storage System (ESS) and local generation. The proposed EMS decides the fraction of the MG energy that must be transferred to the ESS and the residual fraction will be exchanged to the main grid. The main objective is to maximize the profit generated by energy trading with the grid. A day-ahead scheduling is investigated in [5] for an EMS optimal solution. A new strategy based on Fuzzy logic is used to solve the EMS. A dynamic dispatch of BS in MG is investigated in [6]. The problem's objective function is modelled to maximize the operational profit of the battery utilisation. A reinforcement learning combined with Monte-Carlo tree search is proposed to solve the battery management. In [7], the studied MG is composed of PV panels with batteries to ensure the LD consumption. The proposed EMS is based on the State Of Charge (SOC) levels of BS which is limited by minimum and maximum boundaries to avoid the battery over charge and over discharge. In addition, the simulation results are discussed for islanded and GC operations. In [8], an EMS based on model predictive control and quadratic programming is discussed to manage GC-MG with WT farm and battery devices. The main objective is to feed the electricity grid with WT power according to the variations of electricity price and peak periods in a day, by handling efficiently the battery's SOC and charge/discharge cycles. An EMS based on two stage rolling horizon is investigated in [9] for an optimal solution of GC-MG with PV system and BS. The optimization problem is modelled to minimize the grid energy daily cost as well as maximize the consumption of renewable sources. The optimal control setting of the BS is determined by using MILP. In [10], a Multi-population brain storm optimization with differential evolution strategies is investigated to solve total optimization of a smart city. The problem objective function is defined to minimize the energy cost, the actual electric power loads and reduce CO_2 emissions. In [11], an EMS is presented to control the power of each energy source. The EMS is tested for a system with fuel cell power module, BS and supercapacitor. A flower pollination algorithm is investigated in [12] to solve the EMS of GC-MG with integration of RES, micro turbine, fuel cell and BS. The objective function is the minimization of operational cost of BS, cost of generated energy, cost of the energy exchanged with the grid, as well as demand response cost. In [13], a modified Particle Swarm Optimization (PSO) algorithm is proposed to find the optimal operating point of BS in a community MG. A penalty function is introduced for an efficient charging and discharging battery energy.

Most of these research works don't take into consideration the minimization of battery life span as objective function. As demonstrated, the charging and discharging cycles have significant effect on the life span of a BS. For this purpose, this paper incorporates the lifecycle degradation cost as one of the objective functions to be minimized. The Rainflow algorithm is used to count charging-discharging cycles and then quantify the Battery Degradation Cost (BDC). Boqtob et al. [14] have justified the effectiveness of the Hybrid Particle Swarm Optimization with Sine Cosine Acceleration Coefficients (H-PSO-SCAC) to solve the unit commitment of a grid connected MG, The H-PSO-SCAC has better result in terms of convergence accuracy, reliability in searching and efficiency than PSO and GA. In this paper, the H-PSO-SCAC algorithm is used to solve a 48h scheduling of a rural isolated MG units.

The structure of the paper is presented as follows. Section 2 describes MG units modelling, Section 3 presents the proposed EMS including the proposed objective function and system constraints, Section 4 introduces the implementation of H-PSO-SCAC and Rainflow algorithm in the EMS, Section 5 describes Simulation results and discussion, and Section 6 concludes the paper.

2. MG Modelling

The studied MG consists of RES with PV panels, WT units, BS and DGs.

2.1. Photovoltaic Generator

In a simple model, the energy output of a PV is proportional to solar irradiation and can be determined as follows by Eq.(1) [15]:

$$E_{PV} = I_{PV} A_{PV} \eta_{PV} \tag{1}$$

Where I_{PV} is the hourly solar irradiation incident (kWh/m^2) on the PV panels, A_{PV} is the PV panels area (m^2) and η_{PV} is the PV panels efficiency.

The total energy output for a number of PV panels can be defined as follows:

$$E_{PVT} = E_{PV} * N_{PV} \tag{2}$$

Where N_{PV} is the number of PV panels.

2.2. Wind Turbine Generator

The energy output of WT is proportional to Wind Speed (WS) at the hub height, and can mathematically expressed by Eq.(3) [15]:

$$E_{WT} = 0.5\eta_{WT}\rho_{air}C_P A V^3 \tag{3}$$

Where η_{WT} is the WT's efficiency, ρ_{air} is the air density (Kg/m^3), C_P is the power coefficient of WT, A is swept area of WT rotor (m^2), V is the hourly WS (m/s) at hub height.

The hourly WS at hub height can be modelled by Eq.(4) [16]:

$$\frac{V}{V_{ref}} = \left(\frac{h_{hub}}{h_{ref}}\right)^{\alpha} \tag{4}$$

Where V_{ref} is the hourly WS (m/s) measured at the reference height h_{ref} (m), h_{hub} is the hub height (m) and α is the power law exponent ranged in [1/7,1/4], and generally α is considered as 1/7 for an open space [17].

The total energy output for a given number of WT can be expressed as follows:

$$E_{WTT} = E_{WT} * N_{WT} \tag{5}$$

Where N_{WT} is the number of WT generators.

2.3. Battery Energy Storage

The inclusion of BS is desirable to take full advantage of the RES installed in the isolated MG and to provide more energy.

The battery energy is depended to the battery energy at previous time interval and battery average power in the current time interval. Power is subtracted from battery energy at t instant, to increase the amount of available energy, in case of charging mode, or to decrease the available energy in case of discharging mode.

The battery power can be defined according to the battery operation mode as follows:

$$P_{Bat}(t) = P_{Bdch}(t)\rangle 0 \text{ if the battery is discharged.} \tag{6}$$

$$P_{Bat}(t) = P_{Bch}(t)\langle 0 \text{ if the battery is charged.} \tag{7}$$

The battery energy can be defined as follows:

$$E_{Bat}(t+1) = E_{Bat}(t) - (\eta_{Bch} * P_{Bch} + \frac{P_{Bdch}}{\eta_{Bdch}}) * Delta(t) \tag{8}$$

Where P_{Bdch} and P_{Bch} are the battery discharge power and the battery charge power, respectively. η_{Bch} and η_{Bdch} are the battery charge efficiency and the battery discharge efficiency, respectively and *Delta(t)* is the time slot.

The initial value of battery energy is depended on the initial SOC value:

$$E_{Bat}(t=0) = SOC(t=0) * E_{Bat\_usable} \tag{9}$$

The calculation of SOC is deduced from the SOC at previous time interval and power variation over each time interval, with respect to the usable battery energy, taken into consideration charging and discharging modes.

$$SOC(t+1) = SOC(t) - \frac{(\eta_{Bch} * P_{Bch} + \frac{P_{Bdch}}{\eta_{Bdch}}) * Delta(t)}{E_{B\_usable}} \tag{10}$$

Where E_{Bat_usable} is the battery usable energy.

3. EMS Problem Formulation

3.1. Objective Function

3.1.1. Cost of Diesel Energy

Among the energy sources in the studied MG, the energy generated by PV and WT depend on the environment conditions and it is with free generation cost contrary to DG source that requires fuel for electricity production. Therefore, the Fuel Cost (FC) of DGs is defined by F_1 as follows:

$$F_1 = \sum_{t=1}^{T}\sum_{i=1}^{N_{DG}} C_i(P_{DG_i}(t)) \tag{11}$$

Where T is the horizon time, N_{DG} is the number of DGs, and $C_i(P_{DGi}(t))$ is the FC corresponding to DG$_i$.

The FC of each DG at t time is modelled by a quadratic function of DG power output and is expressed by Eq.(12) [18]:

$$C_i(P_{DG_i}(t)) = a_i P_{DG_i}^2(t) + b_i P_{DG_i}(t) \tag{12}$$

Where a_i and b_i are cost coefficients of DG$_i$ and $P_{DGi}(t)$ is the DG$_i$'s power output at t time.

3.1.2. Battery Cost Degradation

The life of battery cells is very sensitive to the charge and discharge cycles of battery operation mode [19], resulting in degradation of the battery life, thus BDC must be included in the operating cost of a battery system [20].

In this paper, an equivalent cycling degradation cost of charging/discharging cycles for a given Depth Of Discharge (DOD) is proposed as the second objective function to be optimized. The degradation cost model of battery system defined by F_2 is employed in [21] as follows:

$$F_2 = \sum_{t=1}^{T} C_{bat\_cyc} * TLL(t, DOD) \tag{13}$$

Where C_{bat_cyc} is the cycling cost involved for charging/discharging cycles from the total investment cost of the battery and *TLL(t,DOD)* is the life loss of the battery over the time period T, for counted cycles of *DOD.*

We will apply the Rainflow algorithm to count the total number of cycles corresponding to cycle *DOD.*

In this paper, the total life lost, *TLL*, from a SOC profile is calculated by summing up the life loss of all *I* number of cycles as follows:

$$TLL = \sum_{i=1}^{I} S_{cyc}(DOD_i) \tag{14}$$

Where $S_{cyc}(DOD)$ is the cycle depth stress function of the battery for charging/discharging operations. It can be defined as follows [22]:

$$S_{cyc}(DOD) = (5.24E-4)DOD^{2.03} \tag{15}$$

Figure 1 illustrates this relationship between cycle life loss and *DOD*, it is observed that the cycle life loss of battery increases with the cycle depth.

The battery life is affected generally by self degradation and cycle degradation. Self degradation is related to the effect of non-operational factors such as temperature, humidity [23]. By contrast, cycle degradation represents the effect of operational factors such as cycle depth, charging and discharging modes [24].

The cycling cost can be determined by taking out the self cost of the total investment cost as follows [21]:

$$C_{bat\_cyc} = C_{Bat\_inv} - C_{SD} \tag{16}$$

Where C_{Bat_inv} represents the total investment cost of the battery and C_{SD} indicates the self-degradation cost of the battery over the time period.

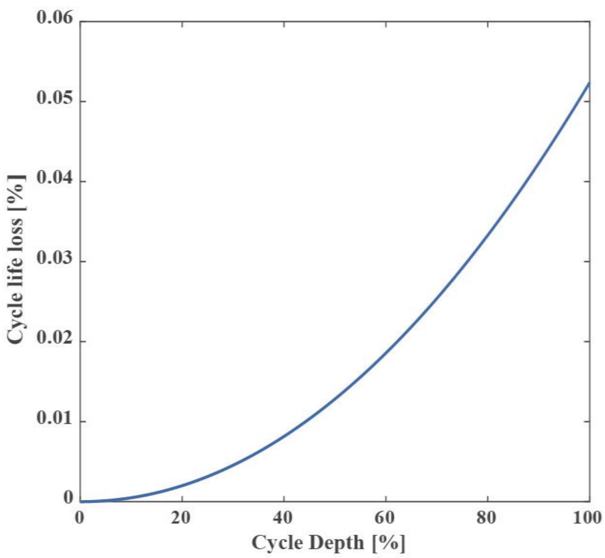

Fig. 1. Cycle life versus depth of discharge of lithium-ion battery.

The total investment cost of the battery can be expressed as follows:

$$C_{Bat\_inv} = N_{Bat} * C_M + N_{Bat} * C_{Bat} * CRF \tag{17}$$

Where N_{Bat} is the number of installed batteries, C_M is the maintenance costs ($/kWh), C_{Bat} is the cost of purchasing the batteries ($/kWh), and *CRF* is the capital recovery factor and can be expressed as follows:

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{18}$$

Where i is the annual real interest rate and n is the battery lifetime.

3.1.3. Combined Diesel Energy Cost with Battery Degradation Cost in the EMS

For the combination of DGs and BS in the EMS of isolated MG, there are two objective functions. One objective function concerns the minimization of the FC of conventional generators. The second objective function concerns the minimization of the degradation cost of the battery. Therefore, the objective function can be formulated as follows:

$$\begin{aligned} F &= m * F_1 + (1-m) * F_2 \\ &= m * \sum_{t=1}^{T} \sum_{i=1}^{N_{DG}} C_i(P_{DG_i}(t)) + (1-m) * \sum_{t=1}^{T} C_{bat\_cyc} * TLL(t,D) \end{aligned} \tag{19}$$

The objective function is subjected to the system constraints presented in the following section. m and 1-m are the weight factors (WFs) and the following condition is obligatory to be satisfied for choosing weight values:

$$m + (1-m) = 1 \tag{20}$$

The minimum value of the objective function represents the economical dispatching of the isolated MG power sources while considering the degradation of the BS.

3.2. Problem Constraints

3.2.1. Power Balance

The power balance constraint, which indicates that all MG power sources including PV and WT, BS unit and DGs should necessarily meet the power LD of the MG at every hour, can be expressed as follows:

$$\sum_{i=1}^{n} P_{DG_i}(t) + P_{WT}(t) + P_{PV}(t) + P_{Bat}(t) = P_{load}(t) \tag{21}$$

Where $P_{DGi}(t)$ is the power output of DG_i at t time interval, $P_{WT}(t)$ is the power generated by WT at time interval t, $P_{PV}(t)$ is the power output of PV panels at time interval t, $P_{Bat}(t)$ is the power of battery at time interval t, and $P_{load}(t)$ is the power of LD at time interval t.

3.2.2. Renewable Generation Limits

The power generated by RES depends on the environment conditions, therefore, the production of PV and WT at time interval t should be maintained within minimum and maximum power limits as follows [25]:

$$P_{PV,\min} \le P_{PV}(t) \le P_{PV,\max} \tag{22}$$

$$P_{WT,\min} \le P_{WT}(t) \le P_{WT,\max} \tag{23}$$

Where $P_{PV,min}$ and $P_{PV,max}$ are the minimum and maximum power limits produced by PV panels, respectively. $P_{WT,min}$ and $P_{WT,max}$ are the minimum and maximum power limits produced by WT, respectively.

3.2.3. Diesel Generator Limits

The power output of DG in time interval t should be maintained within minimum and maximum power limits as in Eq.(24) [18]:

$$P_{DG_i,\min} \le P_{DG_i}(t) \le P_{DG_i,\max} \tag{24}$$

Where $P_{DGi,min}$ and $P_{DGi,max}$ are the minimum and maximum power limits produced by DG_i, respectively.

The power produced by DG is also limited by the physical constraints of starting up and shutting down, which are presented by ramp rate limits, and expressed by Eq.(25) [18]:

$$-DR_i \le P_{DG_i}(t+1) - P_{DG_i}(t) \le UR_i \tag{25}$$

Where DR_i and UR_i are the down-ramp and the up ramp limits of DG_i, respectively.

3.2.4. Battery Constraints

The power of the battery must be within the prescribed charging and discharging power limits at any time:

$$P_{Bch,\max} \langle P_{Bat}(t) \langle P_{Bdch,\max} \tag{26}$$

Where $P_{Bch,max}$ and $P_{Bdch,max}$ are the battery maximum charging power and the battery maximum discharging power, respectively.

The energy level of the battery must be maintained within the minimum and maximum limits at any time:

$$E_{Bat,\min} \langle E_{Bat}(t) \langle E_{Bat,\max} \tag{27}$$

Where $E_{Bat,min}$ and $E_{Bat,max}$ are the minimum and maximum battery energy limits, respectively.

The SOC levels have noticeable effect on battery life; therefore, it is desirable to maintain SOC of the battery within the minimum and maximum limits:

$$SOC_{\min} \langle SOC(t) \langle SOC_{\max} \tag{28}$$

Where SOC_{min} and SOC_{max} are the minimum and maximum battery SOC limits, respectively.

4. EMS Approaches

4.1. Rainflow Algorithm

The Rainflow algorithm can be used in battery stress analysis to count charging-discharging cycles and quantify their cumulative effect. In this paper, the Rainflow is used to count cycles and measure their amplitudes for a given SOC profile [26]. Figure 2 depicts a simple example of SOC profile to apply Rainflow as described below [22]:

1. Start counting and measurement from the beginning of the battery SOC profile.

2. Calculate the absolute value of the difference between two successive turning points as follows: $\Delta d_1 = |d_1 - d_0|$, $\Delta d_2 = |d_2 - d_1|$, $\Delta d_3 = |d_3 - d_2|$ ….

3. A full cycle of depth Δd_2 is determined if $\Delta d_2 \le \Delta d_1$ and $\Delta d_2 \le \Delta d_3$. Then, Remove d_1 and d_2 from the profile, and repeat the process using points d_0, d_3, d_4, d_5 …

4. If a cycle is not determined, shift the identification forward and repeat the process using points d_1, d_2, d_3, d_4 …

5. The process of cycle identification is repeated until no further full cycles can be determined throughout the remaining profile.

The obtained result by applying Rainflow to the example of SOC profile depicted in Fig. 2 is as follows: a discharging half cycle of depth 60% and charging half cycle of depth 60%, one full cycle of depth 50% and two full cycles of depth 20%.

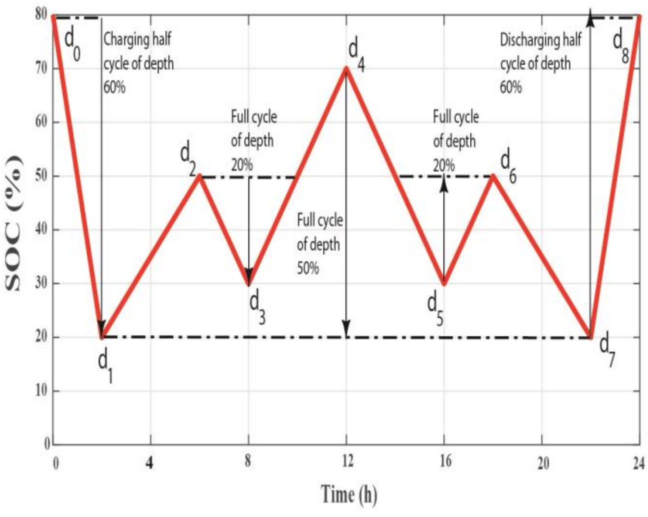

Fig. 2. Example of SOC profile limited between 20% and 80%.

4.2. Hybrid PSO with Sine Cosine Acceleration Coefficient

The Particle Swarm Optimization (PSO) is originally developed by Kennedy and Eberhart in 1995 [27] as nature inspired intelligence algorithm, inspired by social behaviour of organisms in groups. A group of particles are initially searching food in the search area with a random manner, and then look to follow the one that is nearest to the food. In the PSO, each particle is characterised by a fitness value that is computed by the fitness function to be optimized, and has a velocity that defined the move of the particle. The PSO changes the particle position X_i according to the update velocity V_i in every iteration as described by Eq.(29) and Eq.(30) [28]:

$$V_i^{t+1} = w \times V_i^t + c_1 \times r_1 \times (pbest_i^t - X_i^t) + c_2 \times r_2 \times (gbest^t - X_i^t) \quad (29)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (30)$$

Where $w=1$ is the inertia weight, r_1 and r_2 are two uniform distributed numbers ranged in [0,1] and $c_1=c_2=2$ are the acceleration parameters, *gbest* is the global best position discovered by the full population, and $pbest_i$ is the personal best position of particle(i).

The PSO updates the *pbest* and *gbest* as in Eq.(31) and Eq.(32) :

$$pbest_i^t = X_i^t \text{ if } f(X_i^t) \geq f(pbest_i^{t-1}) \quad (31)$$

$$gbest^t = pbest_i^t \text{ if } f(pbest_i^t) \geq f(gbest^{t-1}) \quad (32)$$

Where f is the fitness function to be optimized.

The use of sine cosine acceleration coefficients into the PSO is proposed. The sine map of acceleration coefficients can improve the population diversity into the search process and enhance the convergence ability to the global optimal. C_1 and C_2 are the sine cosine acceleration coefficients, W_{sm} is the sine map inertia weight. The proposed method is called H-PSO-SCAC [29]. In this paper, the H-PSO-SCAC is used to resolve the proposed UC problem. The H-PSO-SCAC updates the particle velocity in every iteration by the following expression:

$$V_i^{t+1} = W_{sm} \times V_i^t + C_1(\times r_1 \times (pbest_i^t - X_i^t) + C_2 \times r_2 \times (gbest^t - X_i^t) \quad (33)$$

In H-PSO-SCAC, the range of W_{sm} is [0,1] , the range of C_1 varies from 2.5 to 0.5 and the range of C_2 varies from 0.5 to 2.5.

4.3. Hybrid PSO with Sine Cosine Acceleration Coefficients

In this paper, the degradation cost of the battery and fuel cost of conventional generators are considered in the objective function. To solve the EMS problem, a combination of two algorithms H-PSO-SCAC and Rainflow is applied. H-PSO-SCAC is used to optimise the objective function while the Rainflow algorithm is used to determine the BDC during the search process.

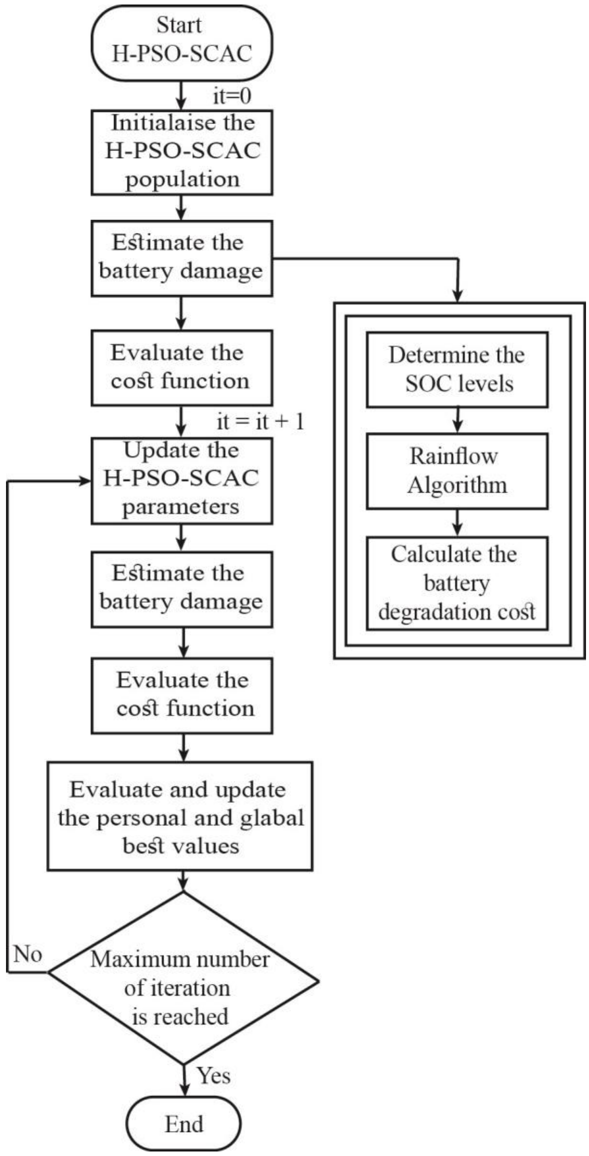

Fig. 3. Flowchart of H-PSO-SCAC and Rainflow algorithm.

The flowchart of the overall H-PSO-SCAC and Rainflow implementation for the EMS problem is shown in Fig.3.

5. Simulation Results and Discussion

5.1. Methodology

To validate the proposed objective function using H-PSO-SCAC, an isolated MG is used with PV panels, WT, battery and two DGs. In this paper, the decision variables are $P_{DG1}(t)$, $P_{DG2}(t)$, $P_{Bat}(t)$, $P_{PV}(t)$ and $P_{WT}(t)$. A 48h-horizon is taken as a scheduling program and the simulation is calculated with a time slot of 1 h. Figure 4 shows the hourly LD for 48h. The average mean LD throughout the day is 6.5 kW. The LD required a higher power between 19h and 22h. The installed WT has 5kW as rated capacity at 10.5m/s wind speed. The WT parameters swept area, air density, and coefficient efficiency are considered as 19.6, 1.225, 0.4, respectively. Figure 5 depicts the WT output power for 48h based on the wind speed data of a site in Taza region at 879 meters altitude above sea level. Figure 6 gives the PV solar power for 48h based on the solar radiation data for a site in Taza region, Morocco (latitude 34.051°N). The used PV solar has 15 kW as rated capacity under the rated environment conditions. The battery parameters used in this paper are depicted in Table 1, it is assumed that the initial battery SOC is already known and taken as 50%. As shown in Table 2, the parameters of the two DGs are presented including fuel cost coefficients, power maximum and minimum limits and ramp rate limits.

The Energy Dispatch (ED) problem is solved by the H-PSO-SCAC. Where, the population size and maximum number of iterations are considered as 50 and 100, respectively. The algorithm is implemented in Matlab environment, using a personal computer with a 2.59 GHz processor and 8 GB RAM, running on Windows 10.

The effectiveness of the proposed objective function using different weighting factor is analyzed by using the Best Cost (BC), the Worst Cost (WC), and the Mean Cost (MC) of the objective function.

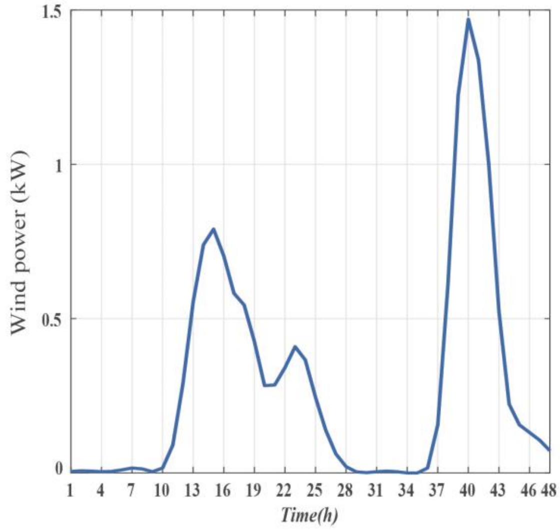

Fig. 5. Wind turbine output power throughout a 48-horizon time.

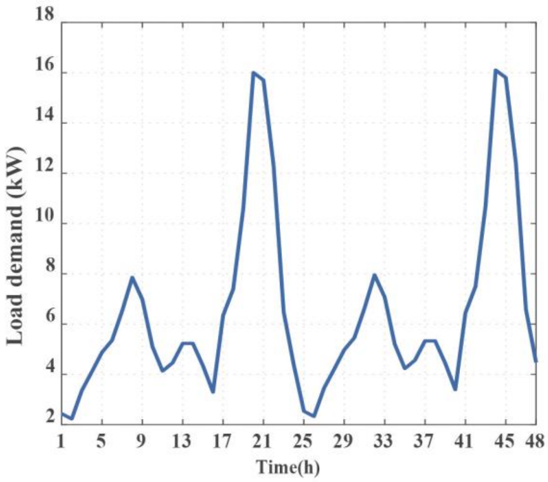

Fig. 4. Load demand of an isolated microgrid throughout a 48-horizon time.

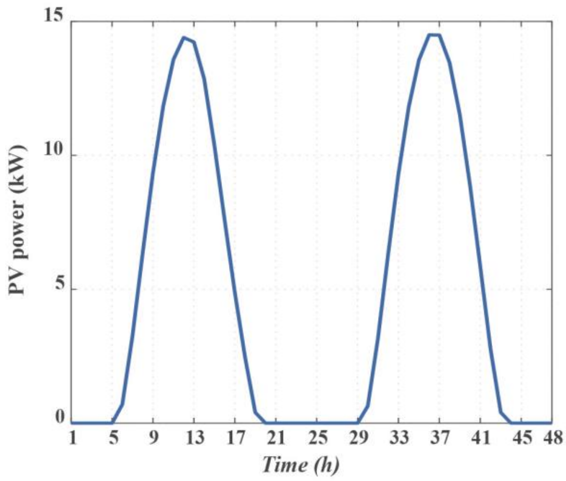

Fig. 6. PV output power throughout a 48-horizon time.

Table 1. Battery parameters

Battery Parameter	Energy capacity (kWh)	Usable capacity (kWh)	Maximum charge power (kW)	Maximum discharge power (kW)	Initial SOC (%)	SOC_{max} (%)
Value	9.8	9.3	7	5	50	80
Battery Parameter	SOC_{min}(%)	Cost of battery ($)	Maintenance cost ($/year)	Interest rate (%)	Lifetime (years)	
Value	20	550	10	6	15	

Table 2. Diesel generators parameters

DG_i	a_i	b_i	$P_{DGi,min}$ (kW)	$P_{DGi,max}$ (kW)	DR_i(kW)	UR_i(kW)
1	0.03	0.25	0	6	5	5
2	0.0001	0.0490	0	10	9	9

5.2. Results and discussion

For the simulation tests, different values of WF are considered in the objective function, in order to evaluate the impact of giving a specified WF to objectives and view its influence on the MG solution. Thus, the impact of WF is analyzed on the algorithm behavior, the status of the SOC of the battery and on the optimized cost fitness function.

5.2.1. Impact of Weight Factor on The Algorithm Behaviour and Cost Fitness Function

The ED problem is solved by the H-PSO-SCAC. Figure 7 illustrates the convergence of the H-PSO-SCAC with implementation of different values of WF (0, 0.5 and 1) on the objective function. When m=1, the objective function is focused on the minimization of fuel cost without giving importance to the BDC. However, when m=0, the objective function is focused on the maximization of the battery life and ignores the fuel cost minimization.

For m=1, the H-PSO-SCAC process has started converging to a local optimum position at 20 trial runs. For m=0.5 it is clearly shown that the H-PSO-SCAC is trapped in the local optimum position after 33 trial runs. However, for m=0 the H-PSO-SCAC can explore more search areas to register the best solution.

The graph proves the impact of WF value on the behavior of the H-PSO-SCAC algorithm, the smaller the value of WF is considered on the objective function, and the smaller the best solution is achieved by the H-PSO-SCAC algorithm.

The optimization criteria of the ED problem using different WF values are described in Table 3. The results are given for m=0, m=0.3, m=0.5, m=0.7 and m=1.

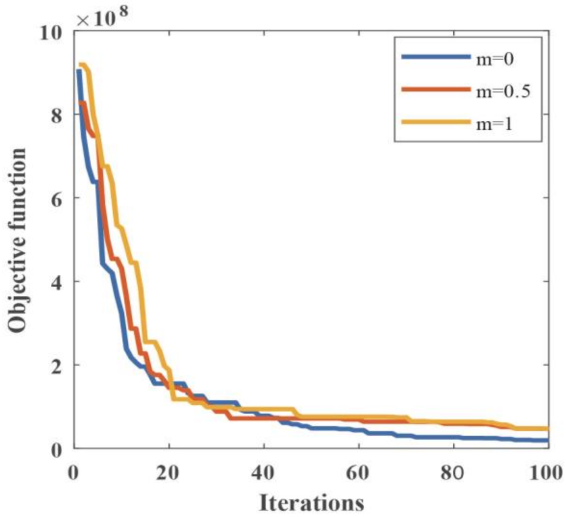

Fig. 7. The convergence of the H-PSO-SCAC using different weight factors on the objective function.

The result demonstrates that the best result with BC and MC is achieved with m=0 the case of the objective is given to maximize the battery life without giving attention to the fuel cost. In addition, in the case of m=1 when the attention is given to minimize the fuel cost and neglect the battery degradation, the ED problem achieve the lowest BC than m=0.3, m=0.5, m=0.7. The results illustrate that to obtain the BC function, the selection of an appropriate value of WF is required.

5.2.2. Impact of Weight Factor on The State of Charge Behaviour

The state of the SOC of the battery is taken as constraint on the ED problem to avoid the over-charging and over-discharging. Figure 8 depicts the impact of WF value on the battery SOC behavior. The objective function is tested with different WF value (0, 0.5 and 1). When m=1, the battery degradation is not important this is clearly shown by several charge and discharge cycles which means that the battery delivers important amount of energy to the MG. However, when m=0, many charge discharge cycles are eliminated and the battery life can be increased. When m=0.5, the objective function balances the trade off's between the two objectives. The graph shows that the state of the SOC is maintained more stable and the charge discharge cycles are clearly reduced. Thus, the amount of the battery exchanged with the MG is reduced, this is why the cost function for m=0.5 is higher than those for m=0 and m=1 as shown in Table 3.

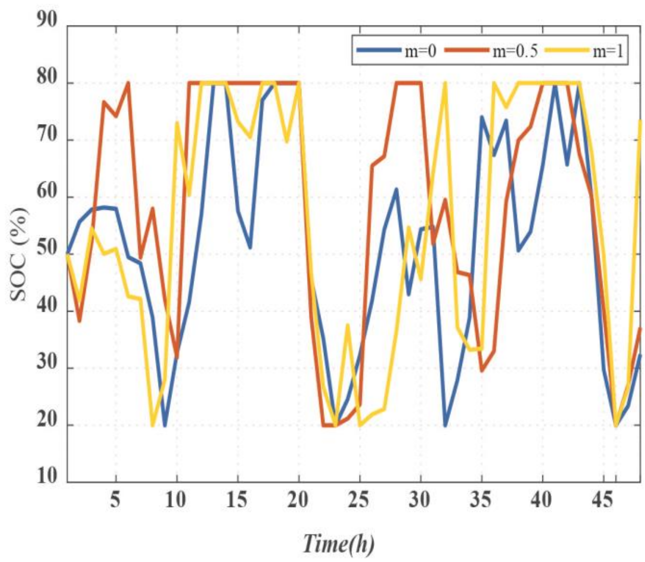

Fig. 8. The impact of weight factor value on the battery SOC behaviour

Table 3. Performance of the objective function using different weight factor values and solved by the H-PSO-SCAC algorithm for 100 trial runs

	m=0	m=0.3	m=0.5	m=0.7	m=1
Best cost ($/day)	9596009	23133127	23559582	25067694	22988968
Average cost ($/day)	22243500	50475000	86945000	67030000	53560000
Worst cost ($/day)	1.0508e+09	1.0980e+09	1.0105e+09	1.0306e+09	9.7360e+08

5.2.3. Energy Dispatch of Microgrid Units with Weight Factor equals to 0.5

The next simulation result of ED problem of MG units is performed for m=0.5 to balance the trade off's between the two objectives. Table 4 depicts the optimal power produced by the two installed DGs solved by the H-PSO-SCAC algorithm. The DGs are taken as the main energy source for the isolated MG, it can be shown from Table 4 that the two DGs generate the energy all over the simulation time, with high production during night, and low one at the morning. Table 5 shows the optimal exchanged power between the MG and the battery obtaining from the H-PSO-SCAC algorithm. It can be seen that the battery is charged when the LD is low; however, the battery is discharged when the LD is high and the Renewable Energy (RE) production is low. In addition, Table 6 details the optimal power generated by RGs $P_{PV}(t)$ and $P_{WT}(t)$ resulting from H-PSO-SCAC algorithm. The renewable production supports the DGs production especially when PV generator and WT generator start producing energy. The most of the RE production charge the battery.

Figure 9 plots the optimal ED solution of MG units during the 48 horizon time as in Table 4, Table 5 and Table 6. It is clearly shown that all the MG units participate to satisfy the LD. When the PV panel and WT generator start generating energy, due to the lower LD, the battery is charged, and DGs reduce their production. As observed from Fig.9, $P_{Bat}(t)$ can be positive or negative. As explained in the paper, $P_{Bat}(t)$ is negative means that the MG charges the battery whilst if $P_{Bat}(t)$ is positive, the battery delivers energy to the MG. When the LD is lower than the energy produced by RE and DGs, the excess power can be delivered to the battery.

Then, when the RE production is reduced and the LD requires more energy during the night period, the DGs and battery can collaborate to fill the need and satisfy the LD.

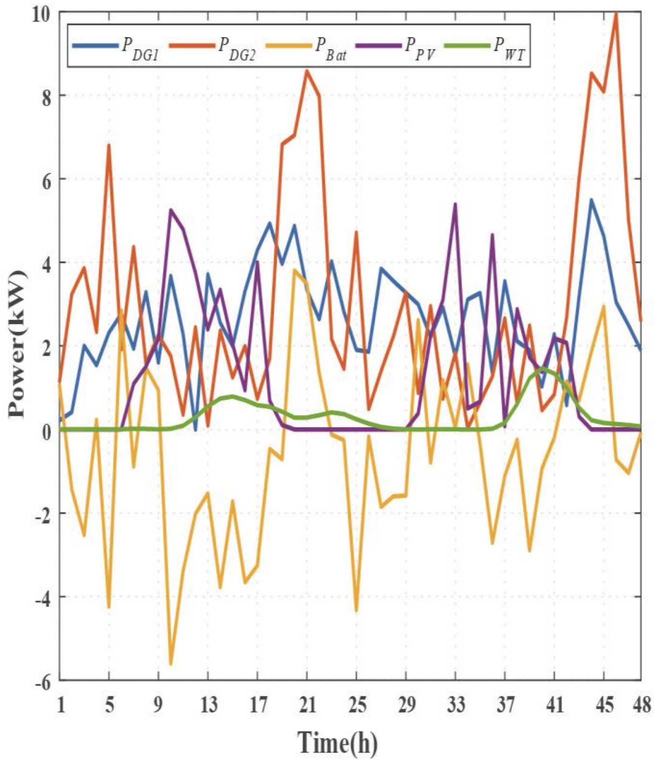

Fig. 9. The resulted ED solution of MG generation units for m=0.5

Table 4. Optimal power produced by diesel generators $P_{DGi}(t)$ by H-PSO-SCAC for m=0.5

Time (h)	P_{DG1} (kW)	P_{DG2} (kW)	Time (h)	P_{DG1} (kW)	P_{DG2} (kW)	Time(h)	P_{DG1} (kW)	P_{DG2} (kW)
1	0.217857	1.126109	17	4.290849	0.733674	33	1.756027	1.826368
2	0.41551	3.238563	18	4.933234	1.697407	34	3.111227	0.032484
3	2.00718	3.866612	19	3.959647	6.8234	35	3.267334	0.646606
4	1.535267	2.337054	20	4.872569	7.04285	36	1.338725	1.270038
5	2.317106	6.790868	21	3.349535	8.579052	37	3.546229	2.658267
6	2.767133	1.919401	22	2.636031	7.97911	38	2.112662	0.625007
7	1.934837	4.363621	23	4.022178	2.164111	39	1.899601	2.485883
8	3.285469	1.568873	24	2.812477	1.45311	40	1.03026	0.458643
9	1.603434	2.256644	25	1.904528	4.709048	41	2.280025	0.838275
10	3.67349	1.759593	26	1.863599	0.492047	42	0.587025	2.677349
11	2.280909	0.355728	27	3.849791	1.398528	43	3.172846	6.007136
12	0	2.44283	28	3.553457	2.230391	44	5.488163	8.526166
13	3.71085	0.096471	29	3.276081	3.279156	45	4.627881	8.085471
14	2.555105	2.363928	30	2.995072	0.876219	46	3.049077	9.949099
15	1.993236	1.241036	31	2.2122	2.950293	47	2.494461	5.018957
16	3.310866	1.998961	32	2.928534	0.739797	48	1.895278	2.586261

Table 5. Optimal power of the battery by H-PSO-SCAC for m=0.5

Time(h)	P_{Bat}(kW)	Time(h)	P_{Bat}(kW)	Time(h)	P_{Bat}(kW)	Time(h)	P_{Bat}(kW)
1	1.086034	13	-1.52839	25	-4.32458	37	-1.10921
2	-1.43607	14	-3.77244	26	-0.17065	38	-0.24767
3	-2.52479	15	-1.72286	27	-1.8544	39	-2.88876
4	0.228678	16	-3.66012	28	-1.59903	40	-0.93912
5	-4.23797	17	-3.2583	29	-1.58424	41	-0.1931
6	2.845105	18	-0.46632	30	2.618075	42	1.15452
7	-0.88431	19	-0.71294	31	-0.79301	43	0.690862
8	1.478395	20	3.80558	32	1.177009	44	1.866671
9	0.945756	21	3.490413	33	0.049985	45	2.934648
10	-5.59993	22	1.347859	34	1.555535	46	-0.72518
11	-3.38707	23	-0.12129	35	-0.35182	47	-1.04442
12	-2.01944	24	-0.25759	36	-2.71099	48	-0.07854

Table 6. Optimal power produced by renewable generators $P_{WT}(t)$ and $P_{PV}(t)$ by H-PSO-SCAC for m=0.5

Time (h)	P_{PV} (kW)	P_{WT} (kW)	Time (h)	P_{PV} (kW)	P_{WT} (kW)	Time (h)	P_{PV} (kW)	P_{WT} (kW)
1	0	0.005	17	3.995774	0.582	33	5.383937	0.004
2	0	0.007	18	0.685681	0.544	34	0.500754	0
3	0	0.006	19	0.107896	0.426	35	0.667876	0

4	0	0.004	20	0	0.283	36	4.646229	0.016
5	0	0.005	21	0	0.285	37	0.078713	0.156
6	0	0.005018	22	0	0.341	38	2.878142	0.611
7	1.093852	0.017	23	0	0.41	39	1.723273	1.224
8	1.509264	0.013	24	0	0.367	40	1.374222	1.47
9	2.167166	0.004	25	0	0.246	41	2.181803	1.337
10	5.25085	0.016	26	0	0.14	42	2.074106	1.001
11	4.79016	0.090272	27	0	0.06108	43	0.309156	0.524
12	3.745608	0.291	28	0	0.020183	44	0	0.223
13	2.396065	0.555	29	0	0.004	45	0	0.156
14	3.343408	0.74	30	0.380989	0.001	46	0	0.131
15	2.042591	0.79	31	2.251519	0.004	47	0	0.106
16	0.94129	0.703	32	3.103661	0.006	48	0	0.072

6. Conclusion

This paper describes a scheduling interval of 48h horizon time for energy dispatch of an isolated MG with battery storage. Battery degradation cost is proposed in the objective function in addition to the fuel cost. The energy dispatch problem focused on minimization of the FC of DGs and the BDC. A WF is implemented in the proposed objective function. The energy dispatch problem is solved by H-PSO-SCAC for an optimal dispatch of an isolated MG including WT generator, PV, two DGs and battery storage. The load demand is mainly supplied by the two DGs, and the RGs and battery have been used to reduce the fuel consumption. The analyse of WF impact on the H-PSO-SCAC behaviour is examined by using the BC, the WC, and the MC of the OF, as well as the algorithm convergence. The results illustrate that to obtain the best cost function, the selection of an appropriate value of WF is required. The state of battery SOC is also influenced by WF. The result demonstrates that the battery SOC is more stable with WF equals to 0.5 and the charge discharge cycles are reduced. To balance the trade off's between the BDC and the FC, the ED problem of MG generation units is performed for m=0.5. The H-PSO-SCAC combines all the MG units together to participate in order to satisfy the LD.

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