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Abstract- Nowadays, microgrid applications are proliferate all around the world. Owing to many grounds, such the ease of control, the high efficiency and reliability, the improvement of power electronics devices, the rise of DC type loads and sources, etc. researchers' interest was diverted from AC to DC microgrids. Yet, on a global control and management level, several challenges are confronted. A variety of objectives can be achieved by controlling the power flow of each of the distributed energy sources. By means of this, an optimization problem is formulated and solved using heuristic methods such the genetic algorithm (GA), the particle swarm optimization (PSO), the pattern search (PS), etc. However, other techniques were exploited in the literature such the dynamic programming (DP) which is a step-by-step optimization algorithm. In this paper, a (DP) technique is applied to solve a multi-objective optimization problem. Two objectives are set: DC microgrid operation cost minimization, and pollutant gas emissions reduction. A sole cost function is established, and weights are assigned to each of the predefined goals. Besides, each objective function is detailed apart, and several constrains are set. Two simulations tests are performed to prove the convergence, and the viability of the applied (DP) technique. Finally, different weights are selected in each of simulation tests to validate the effectiveness, and robustness of the (DP) in solving such problems.

I. INTRODUCTION

Over the past few years, microgrid applications have emerged and expanded worldwide owing to several motifs such, the increasing demand for power electricity in all fields, the rising integration of renewable energy sources (RESs) as alternatives to traditional pollutant ones, the high merits of distributed energy generation over traditional centralized approach in terms of reliability, robustness, expandability, etc. [1]. Besides, the rapid development of power electronic devices, and the considerable growth in DC-type loads, sources, and energy storage systems diverted the attention of researchers to DC microgrids [2]. Despite the ease of control of a DC microgrid on a primary control level, compared to AC counterparts [3], many challenges arise if advanced functionalities and objectives are to be achieved on the global power management level. In such instances, an optimization problem is formulated to reach certain predefined goals. The literature proposes various optimization techniques for the energy management of DC microgrids. Heuristic methods such as the genetic algorithm (GA), particle swarm optimization (PSO), pattern search (PS), simulated annealing (SA), etc. are utilized to solve these kinds of problems. In [4] an adaptive (PSO) technique is

used to consider the uncertainties in the optimal energy management of a microgrid. Isolation niche immune genetic algorithm (INIGA) is proposed in [5] to optimize the economic operation of the microgrid as well as to minimize toxic gas emissions. However, a multi-objective adaptive modified particle swarm optimization algorithm (AMPSO) is presented in [6] for the optimal operation of a typical microgrid with (RESs). To minimize the operation cost, and the pollutants emission, two objective functions are set along with constraints. Despite their efficiency in finding global minimums, such heuristic methods require an excessive computational burden and are time-consuming especially in problems with a high number of decision variables.

Meanwhile, dynamic programming (DP) is a step-by-step optimization technique based on restrained research domains. It has been widely used in the literature and yields similar and comparable results to heuristic methods in terms of algorithm convergence, global minimum attainment, and multi-objective achievement [7],[8]. In this paper, a multi-objective optimization problem is formulated and solved using a (DP) algorithm. Two main objectives are set: DC microgrid operation cost minimization, and pollutant gas emissions reduction. A sole cost function is evaluated and minimized. The two mentioned goals are reached with a preference degree defined through fixed weights. These weight variables are included in the basic cost function. The rest of this paper is organized as follows: in section II the DC microgrid model is presented in detail. The optimization problem is formulated in section III. Simulation tests and results are performed in section IV. Finally, section V concludes the paper.

II. 24-HOUR DC MICROGRID MODELLING STRATEGY

The adopted DC microgrid topology is shown in Fig.1. It consists of renewable energy sources (RESs): a solar PV array, and a wind turbine, a lithium-ion battery as an (ESS), a backup diesel generator (DG) as a pollutant source, and DC loads. The DC microgrid can operate in islanded as well as in grid-connected mode to either buy or sell energy from/to the utility grid. Next, each energy source is modeled separately.

A. PV Array

The (RESs), as non-dispatchable sources, are continuously functioning in maximum power point tracking (MPPT) mode. The PV output power function at time k is expressed as [9]:

$$P_{PV}(k) = P_{STC} \times \frac{G_{IN}(k)}{G_{STC}} \times (1 + \alpha(T_C(k) - T_R)) \quad (1)$$

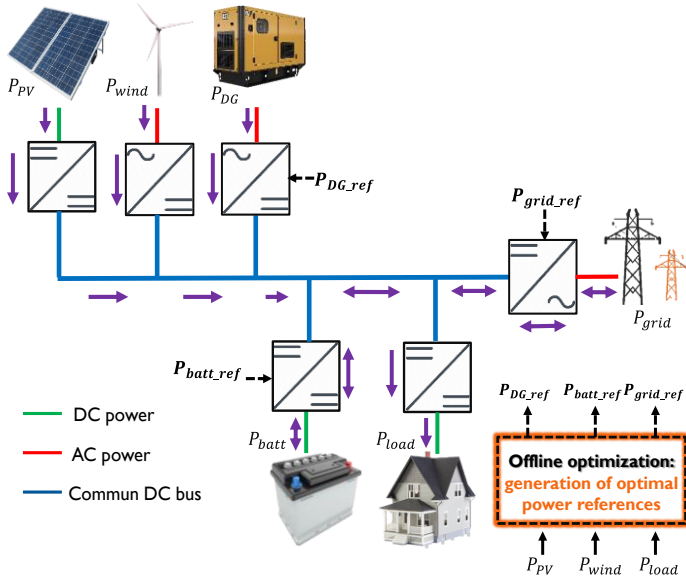


Fig.1 DC microgrid configuration

where, P_{STC} , $G_{IN}(k)$, G_{STC} , α , $T_C(k)$, and T_R are respectively the maximum power at standard test conditions (STCs), the incident irradiation at time k , the irradiation at (STCs), the temperature coefficient, the cell temperature at time k , and the cell temperature at (STCs).

B. Wind turbine

As prementioned, the wind turbine (WT) is operating in MPPT mode. The (WT) output power function can be expressed as [10]:

$$P_{wind}(k) = \begin{cases} 0 & 0 \leq V(k) < V_{ci} \\ a \cdot V(k) - b & V_{ci} \leq V(k) < V_{\alpha} \\ c \cdot V(k)^3 & V_{\alpha} \leq V(k) < V_r \\ d \cdot V(k) - e & V_r \leq V(k) < V_{\beta} \\ P_{wind_r} & V_{\beta} \leq V(k) < V_{co} \\ 0 & V(k) \geq V_{co} \end{cases} \quad (2)$$

where $V(k)$, V_{ci} , V_{co} , V_{α} , V_{β} , and P_{wind_r} are respectively, the wind speed at time k , the cut-in speed, the cut-out speed, the lower limit linear speed, the upper limit linear speed, and the rated wind power. a , b , c , d , and e are constants defined based on the (MPPT) characteristic curve of the (WT).

C. Lithium-ion battery dynamic model

A lithium-ion battery is selected as an (ESS) due to its compliance with such applications. The battery applied model is that figuring in the Simscape library of MATLAB/Simulink, and originally proposed in [11]. The discrete equation of the battery state of charge is expressed as:

$$SOC(k+1) = SOC(k) - \frac{P_{dis}(k) \cdot T_s}{\eta_{dis} \cdot C_{batt} \cdot V_{batt}(k)} - \frac{P_{ch}(k) \cdot \eta_{ch} \cdot T_s}{C_{batt} \cdot V_{batt}(k)} \quad (3)$$

where SOC , $P_{dis}(k)$, $P_{ch}(k)$, $V_{batt}(k)$, C_{batt} , η_{dis} , η_{ch} , T_s are respectively the battery state of charge in (%), the discharged

Algorithm 1 : Battery dynamic model

$[SOC(k+1), V_{batt}(k+1), it(k+1)] = f_{batt}(SOC(k), P_{batt}(k), V_{batt}(k), it(k))$

- 1- $i_{batt}(k) = \frac{P_{batt}(k)}{V_{batt}(k)}$; % battery current in A
- 2- Computing $i_{batt}^*(k)$ from $i_{batt}(k)$ % low frequency current dynamics in A
- 3- $it(k+1) = it(k) + i_{batt}(k) \cdot T_s$; % extracted capacity in Ah
- 4- if ($i_{batt}(k) > 0$) % testing charge/discharge mode
- 5- $P_{ch}(k) = 0$;
- 6- $P_{dis}(k) = P_{batt}(k)$; } % setting discharge mode
- 7- Computing $V_{batt}(k)$ following the expressions in [11]:
 $V_{batt}(k) = f_{dis}(it(k), i_{batt}^*(k), i_{batt}(k)) - R_{batt} \cdot i_{batt}(k)$;
- 8- else
- 9- $P_{dis}(k) = 0$;
- 10- $P_{ch}(k) = P_{batt}(k)$; } % setting charge mode
- 11- Computing $V_{batt}(k)$ following the expressions in [11]:
 $V_{batt}(k) = f_{ch}(it(k), i_{batt}^*(k), i_{batt}(k)) - R_{batt} \cdot i_{batt}(k)$;
- 12- end
- 13- Computing $SOC(k+1)$ using equation (3)
- 14- end

power at time k in (W), the charged power at time k in (W), the battery voltage at time k in (V), the battery rated capacity in (Ah), the discharging efficiency, the charging efficiency, and the sampling time in hours. At each time step, a function f_{batt} is called to compute the battery electrical components following the expressions in [11]. Then, the battery state of charge is deduced using equation (3). The function script is represented in algorithm.1.

III. OPTIMIZATION PROBLEM FORMULATION

In this section, the optimization problem is formulated and solved using the (DP) algorithm. The two main objectives to be attained are: minimizing the total operation cost of the DC microgrid and minimizing the pollutant gas emissions.

A. Objective function

There are several methods to solve these kinds of optimization problems. One is to set distinct objective functions corresponding to each of the predefined goals and minimize them. Another simple way is to scalarize the set of objectives into a single function by multiplying each objective by a fixed weight. This method is known as the weighted sum method. Besides the reduction of the complexity of the problem, it offers to the user the possibility of objectives' preference through the selected weights. Therefore, the total objective function is the sum of weighted cost functions of the total operating cost, and the pollutant gas emissions. It can be expressed as follow:

$$J_{tot} = \gamma_{oc} \cdot J_{oc} + \gamma_{emissions} \cdot J_{emissions} \quad (4)$$

where J_{tot} , J_{oc} , $J_{emissions}$, γ_{oc} , and $\gamma_{emissions}$ are respectively the total objective function in \$, the operation cost function in \$, the pollutant gas emissions cost function in \$, the operation cost weight, and the pollutant gas emissions weigh.

A.1. Total operating cost function

The total operating cost function is the sum of the (RES)s cost

function, the power grid cost function, the battery storage cost function, and the diesel generator cost function.

$$J_{oc} = J_{RESS} + J_{grid} + J_{batt} + J_{DG} \quad (5)$$

1) (RES)s cost function: it consists of the operation and maintenance (O&M) costs of the (RES)s:

$$J_{RESS} = J_{PV}^{O\&M} + J_{WT}^{O\&M} \quad (6)$$

where J_{RESS} , $J_{PV}^{O\&M}$, and $J_{WT}^{O\&M}$ are respectively, the (RES)s cost function in \$, the (O&M) cost of the PV in \$, and the (O&M) cost of the WT in \$. $J_{PV}^{O\&M}$ and $J_{WT}^{O\&M}$ can be calculated as:

$$J_{PV}^{O\&M} = \sum_{k=1}^N \delta_{PV}^{O\&M} \cdot P_{PV}(k) \cdot T_s \quad (7)$$

$$J_{WT}^{O\&M} = \sum_{k=1}^N \delta_{WT}^{O\&M} \cdot P_{WT}(k) \cdot T_s \quad (8)$$

where N , $\delta_{PV}^{O\&M}$, $\delta_{WT}^{O\&M}$ are respectively, the time horizon steps, the (O&M) costs per KWh of the PV, and the WT ($\delta_{PV}^{O\&M} = 0.0024$ \$/KWh, and $\delta_{WT}^{O\&M} = 0.0098$ \$/KWh).

2) Power grid cost function: it can be expressed as the difference between the purchased energy from the utility grid and the sold energy to the utility grid over the 24 hours' time horizon.

$$J_{grid} = \sum_{k=1}^N \left(\delta_{grid}^{pur} \cdot P_{pur}(k) - \delta_{grid}^{sold} \cdot P_{sold}(k) \right) \cdot T_s \quad (9)$$

where δ_{grid}^{pur} , δ_{grid}^{sold} , $P_{pur}(k)$, and $P_{sold}(k)$ are respectively the purchased electricity cost per KWh (δ_{grid}^{pur} is the electricity pool price, and is represented in Fig.4), the sold electricity cost per KWh ($\delta_{grid}^{sold} = 0.068$ \$/KWh), the purchased electricity power at time k , and the sold electricity power at time k . $P_{pur}(k)$ and $P_{sold}(k)$ are expressed as functions of the grid power $P_{grid}(k)$ at time k as follows:

$$P_{pur}(k) = P_{grid}(k) \cdot \max(\text{sign}(P_{grid}(k)), 0) \quad (10)$$

$$P_{sold}(k) = P_{grid}(k) \cdot \min(\text{sign}(P_{grid}(k)), 0) \quad (11)$$

By using (10) and (11), the purchased and sold electricity at any time are deduced from the utility grid power which, reduces the number of decision variables. By referring to (10) and (11), $P_{pur}(k)$ is equal to $P_{grid}(k)$ and $P_{sold}(k)$ is null when $P_{grid}(k)$ is positive whereas, $P_{pur}(k)$ is set to zero and $P_{sold}(k)$ is equal to $-P_{grid}(k)$ when $P_{grid}(k)$ is negative. Thereby, the grid electricity cannot be purchased and sold at the same time k .

3) Battery storage cost function: the battery lifetime is represented as the number of charges and discharges cycles. Hence, to quantify the storage operating cost, one way is to divide the battery capital cost per KWh over the number of cycles to obtain the battery operating cost per cycle. In

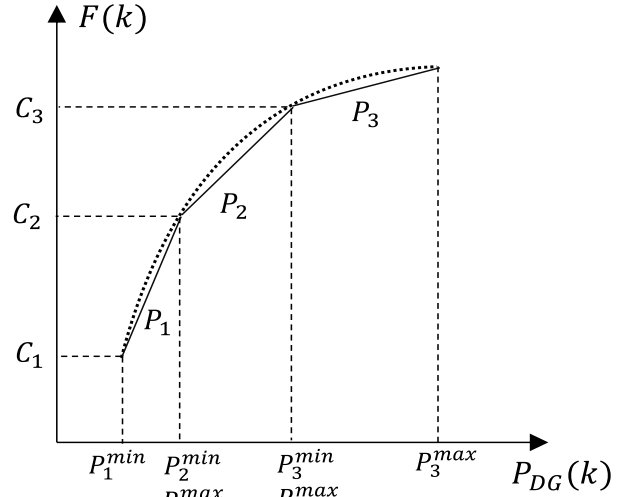


Fig.2 Piecewise approximation of the (DG) fuel consumption function

addition, the battery degradation issue is added to the operating cost function as expressed in [12]:

$$J_{batt} = \sum_{k=1}^N \left(\frac{CC}{2 \cdot Cycles} \cdot P_{batt}(k) \cdot T_s + \delta_{deg} \cdot P_{batt}^2(k) \cdot T_s \right)$$

where CC , $Cycles$, $P_{batt}(k)$, δ_{deg} are respectively the battery capital cost per KWh ($CC=135.38$ \$/KWh), number of life cycles ($Cycles=1000$ for a depth of discharge $DoD=80\%$), battery power at time k , and the degradation cost ($\delta_{deg}=10^{-9}$ \$/W²h).

4) Diesel generator cost function: the (DG) total cost function J_{DG} consists of the fuel consumption cost function J_{DG}^{fuel} , the start-up cost function J_{DG}^{SU} , and the maintenance cost function J_{DG}^M . It can be expressed as:

$$J_{DG} = J_{DG}^{fuel} + J_{DG}^{SU} + J_{DG}^M \quad (12)$$

A piecewise approximation of the fuel consumption, proposed in [13], is applied. The piecewise linearized fuel consumption function is shown in Fig.2. For more details on the approximation method, it can be referred to [13]. Thus, the fuel consumption cost can be expressed as:

$$J_{DG}^{fuel} = \sum_{k=1}^N \lambda_{fuel} \cdot F(k) \cdot T_s \quad (13)$$

where λ_{fuel} , $F(k)$ are respectively the price of diesel per liter ($\lambda_{fuel} = 1.05$ \$/L), and the fuel consumption in L/h. Knowing $P_{DG}(k)$, $F(k)$ is determined based on the plotted curve in Fig.2. The constant parameters are defined in table 2. The start-up cost function J_{DG}^{SU} corresponds to the fuel consumed during the start-up phase before any power production. The start-up cost is the cost per start-up ($\xi_{SU} = 0.011$ \$) times the number of start-ups over the time horizon. This can be calculated as:

$$J_{DG}^{SU} = \xi_{SU} \cdot \sum_{k=1}^N \sigma_{DG}^{ON}(k) \quad (14)$$

where $\sigma_{DG}^{ON}(k)$ is a binary variable equal to one when the (DG) is turned-on at time k and zero otherwise. $\sigma_{DG}^{ON}(k)$ is defined as:

$$\sigma_{DG}^{ON}(k) = \max(\text{sign}(P_{DG}(k+1)) - \text{sign}(P_{DG}(k)), 0) \quad (15)$$

Finally, the maintenance cost depends on the operation time of the (DG). It can be calculated as the maintenance cost per hour ($\chi_M = 0.03$ \$/h) times the total operating hours of the (DG):

$$J_{DG}^M = \chi_M \cdot \sum_{k=1}^N \text{sign}(P_{DG}(k)) \cdot T_s \quad (16)$$

A.2. Pollutant gas emissions cost function

Fossil fuel consumption produces toxic gases such NO_x , CO_2 , CO , and SO_2 . These gas emissions are the main source of air pollution and greenhouse. The pollution aspect can be considered by introducing the quantity of emitted toxic gases in a (DG) application, (α) expressed in (g/KWh), and the expenses related to environmental damages resulting from the pollutant gas emissions, (μ) expressed in (\$/Kg) [14]. All parameters' values are listed in table 1. Thereby, the pollutant gas emissions cost function can be represented as:

$$J_{emissions} = \beta_{emiss} \cdot \sum_{k=1}^N P_{DG}(k) \cdot T_s \quad (17)$$

$$\beta_{emiss} = (\alpha_{NO_x} \cdot \mu_{NO_x} + \alpha_{CO_2} \cdot \mu_{CO_2} + \alpha_{CO} \cdot \mu_{CO} + \alpha_{SO_2} \cdot \mu_{SO_2}) \cdot 10^{-3} \quad (18)$$

B. Problem constraints

Several constraints are set to emulate a realistic and practical microgrid scenario. Next, constraints for each microgrid unit are detailed apart.

B.1. Power balance constraint

At each sampling time k , the generated power should be equal to the demanded one. This is known as the power balance equation:

$$P_{PV}(k) + P_{WT}(k) + P_{batt}(k) + P_{grid}(k) + P_{DG}(k) = P_{load}(k) \quad (19)$$

We take note that $P_{PV}(k)$, $P_{WT}(k)$, and $P_{DG}(k)$, as energy sources, are always positive. Similarly, $P_{load}(k)$ is positive and set on the right side of the equation. However, $P_{batt}(k)$, and $P_{grid}(k)$ can either have positive or negative values. When positive, $P_{batt}(k)$ corresponds to power charged into the battery, and $P_{grid}(k)$ to the power sold to the utility grid. However, when they are negative, $P_{batt}(k)$ corresponds to the power discharged from the battery, and $P_{grid}(k)$ to the power purchased from the utility grid.

B.2. Utility grid constraints

Lower and upper bounds are fixed to limit the purchased/sold from/to the utility grid power. This can be represented as:

$$P_{grid_min} \leq P_{grid}(k) \leq P_{grid_max} \quad (20)$$

Emission levels (g/KWh)	Toxic gas emissions			
	α_{NO_x}	α_{CO_2}	α_{CO}	α_{SO_2}
	4.331	232.037	2.32	0.464
Cost (\$/Kg)	μ_{NO_x}	μ_{CO_2}	μ_{CO}	μ_{SO_2}
	0.27	0.0012	0.022	0.12

Table 1. Toxic gas emissions in (g/KWh) in a (DG) application, and related environmental expenses in (\$/Kg)

where P_{grid_min} , and P_{grid_max} are respectively the maximum allowable power to be sold to the utility grid ($P_{grid_min} = -P_{max_sold}$), and the maximum allowable power to be purchased from the utility grid ($P_{grid_max} = P_{max_pur}$). P_{max_sold} and P_{max_pur} are positive parameters.

B.3. Battery storage constraints

To ensure an optimized battery lifetime and performance, several constraints are set. First, the battery power is restricted in terms of maximum charged/discharged power:

$$P_{batt_min} \leq P_{batt}(k) \leq P_{batt_max} \quad (21)$$

where P_{batt_min} , and P_{batt_max} are respectively the maximum allowable power to be charged into the battery ($P_{batt_min} = -P_{max_ch}$), and the maximum allowable power to be discharged from the battery ($P_{batt_max} = P_{max_disch}$). P_{max_ch} and P_{max_disch} are positive parameters.

Second, the battery safe operation is ensured by limiting its state of charge (SOC) within allowable limits:

$$SOC_{min} \leq SOC(k) \leq SOC_{max} \quad (22)$$

where SOC_{min} , and SOC_{max} are respectively the minimum, and the maximum allowable (SOC)s.

Finally, the battery initial state at time ($k = 1$) should be retrieved at the end of the time horizon ($k = N$) to further standardize and optimize the battery performance:

$$SOC(k = 1) = SOC(N) \quad (23)$$

B.4. (DG) constraints

For proper and efficient operation, (DG) manufacturers define an output power range for generators. Then, when turned on, the (DG) operation is limited by lower and upper bounds (in this paper a range between 25%-100% of the rated power is applied). This can be expressed as:

$$\text{sign}(P_{DG}(k)) \cdot P_{DG_min} \leq P_{DG}(k) \leq \text{sign}(P_{DG}(k)) \cdot P_{DG_max} \quad (24)$$

Besides, and following the predefined objectives, the (DG), as a backup pollutant source, intercepts to directly feed the load in case of an energy deficit, and/or to charge the battery. Hence, at each time k none of (DG) produced power should be sold to the utility grid. By this, the (DG) main functionality is secured. This can be expressed as:

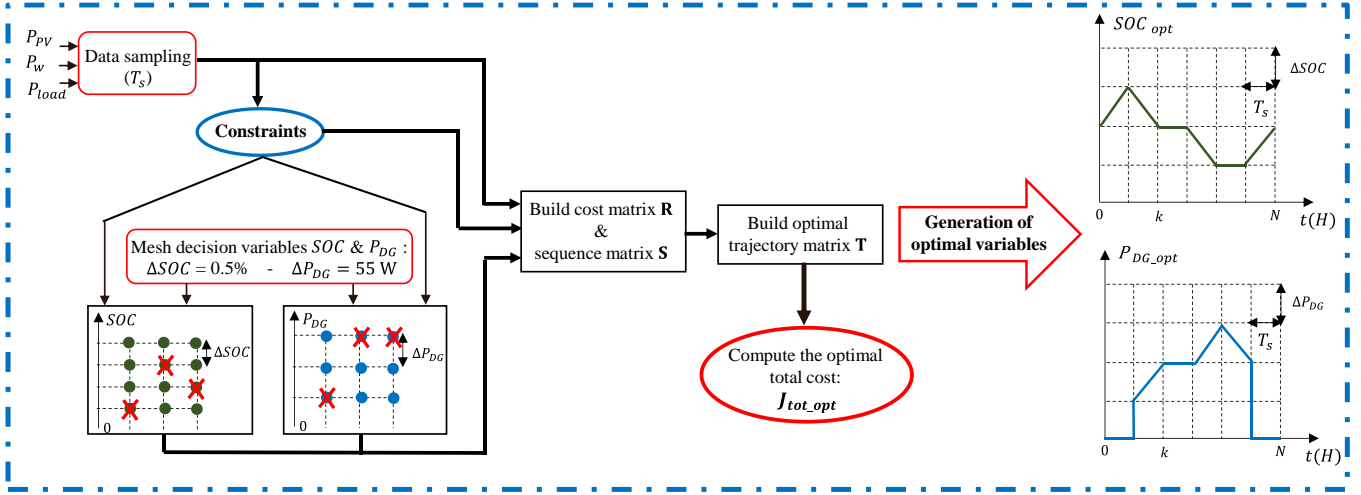


Fig.3 Block diagram of the (DP) adopted algorithm

$$P_{DG}(k) \leq \text{sign}(P_{DG}(k)) \cdot (P_{load}(k) - P_{PV}(k) - P_{WT}(k) + P_{batt}(k)) \quad (25)$$

Finally, Fig.3 shows the block diagram of the (DP) adopted algorithm. First, the input data are sampled at each period T_s , and all constraints are evaluated. Second, the selected decision variables (P_{DG} and SOC) are meshed correspondingly to the defined sampling steps ($\Delta SOC = 0.5\%$, and $\Delta P_{DG} = 55 W$). It's worth mentioning that the selection of the sampling steps of each variable is instrumental, and thoroughly impacts the algorithm convergence, the simulation time, and results' accuracy. Thereby, several trials were made to define the best trade-off between the simulation time and results' precision. Samples that don't satisfy the constraints are rejected, and the remaining ones are used to build the cost and the sequence matrices. At the last stage, the optimal trajectory matrix is established next, the optimal variables, over the whole-time horizon, and the optimal total cost are deduced. For further information on (DP) algorithm, it can be referred to [7-8].

IV. SIMULATION TESTS AND RESULTS

In this section, simulation tests are performed to validate the results of the proposed optimization problem. Therefore, a real case scenario is applied with precise weather conditions, residential load demand, and electricity pool price. The solar power, the wind power, the load demand, and the pool price are depicted in Fig.4. To prove the viability of the applied (DP), two simulation tests are conducted.

Simulation test 1: in this simulation, the minimization of the total operating cost is selected, as a primary goal, over the reduction of pollutant gas emissions. This can be reached by setting a high weight for the operating cost function ($\gamma_{oc} = 0.9$ and $\gamma_{emissions} = 0.1$).

Simulation test 2: in this simulation, the minimization of the pollutant gas emissions is set as a preferred goal. Hence, a higher weight is attributed to the gas emissions cost function ($\gamma_{oc} = 0.02$ and $\gamma_{emissions} = 0.98$). As seen, a high ratio between the two weights is set ($\gamma_{emissions}/\gamma_{oc}=49$) to prioritize

T_s (Hours)	1/6
Wind turbine rated power (KW)	49.5
PV array rated power (KW)	50
(DG) rated power (KW)	55
(DG) power limits (KW)	$P_{DG_{min}} = 13.75$ $P_{DG_{max}} = 55$
Battery rated capacity, voltage, and efficiencies	500 Ah - 250 V $\eta_{dis} = \eta_{ch} = 1$
Battery SOC limits	$SOC_{min} = 20\% - SOC_{max} = 90\%$ $SOC(1) = 50\%$
(DG) fuel consumption function parameters: P (KW), and C (L/h)	$P_{1_{min}} = 13.75, P_{2_{min}} = 25.5$ $P_{3_{min}} = 37.6, P_{3_{max}} = 55$ $C_1 = 6.4, C_2 = 11.41, C_3 = 15$
Utility grid power limits (KW)	$P_{grid_{min}} = -30$ $P_{grid_{max}} = 60$
Battery power limits (KW)	$P_{batt_{min}} = -54.25$ $P_{batt_{max}} = 54.25$

Table 2. DC Microgrid parameters and data

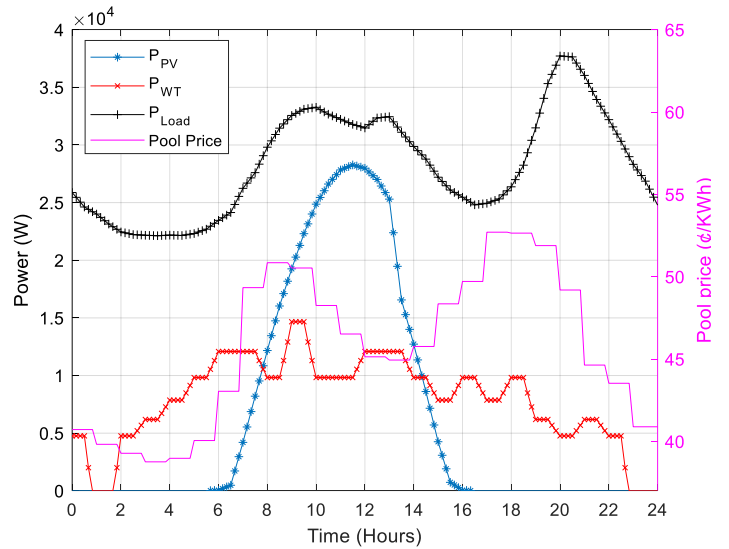


Fig.4 P_{PV} , P_{WT} , P_{load} , and pool price profiles over 24 hours' time horizon

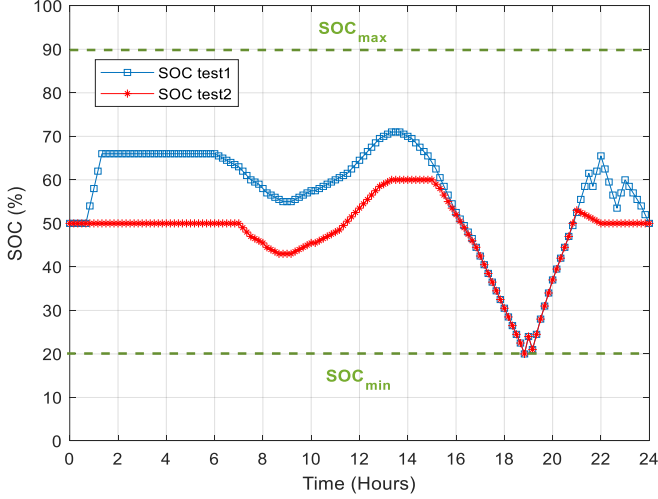


Fig.5 SOC optimal trajectories in test 1 (blue line), and test 2 (red line)

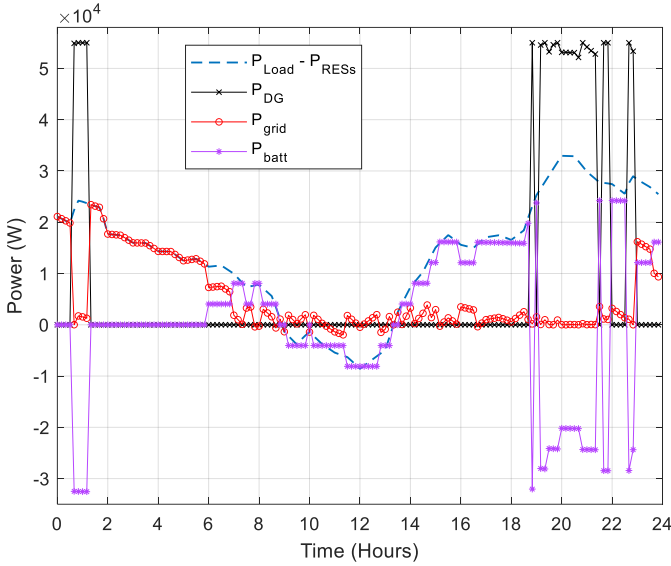


Fig.6.a Optimal P_{DG} , P_{grid} , and P_{batt} profiles (test 1)

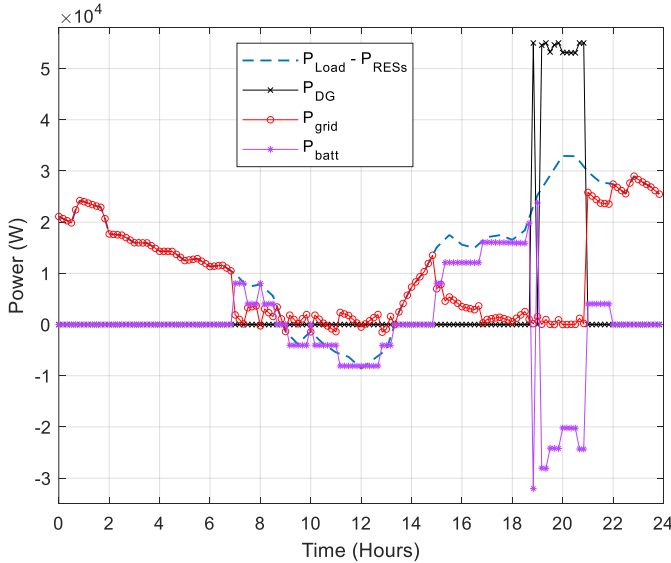


Fig.6.b Optimal P_{DG} , P_{grid} , and P_{batt} profiles (test 2)

	Test 1	Test 2
RESs operating cost	(\$ 2.25)	(\$ 2.25)
Grid operating cost	(\$ 52.33)	(\$ 95.2)
Battery operating cost	(\$ 21.75)	(\$ 12.27)
DG operating cost	(\$ 65.04)	(\$ 33.92)
DG total operating hours	3.83 hours	2 hours
Total pollutant gas emissions	49.6 Kg	25.9 Kg
Total emissions cost	(\$ 0.29)	(\$ 0.15)
Total cost	(\$ 141.67)	(\$ 143.79)

Table 3. Simulation tests results

the emissions reduction goal over the total operating cost. This can be explained by the low average energy cost per KWh of emissions reduction goal ($\delta_{emiss}^{avg} \approx 0.8 \text{ ¢/KWh}$) compared to a higher average energy cost per KWh of total operating cost goal ($\delta_{oc}^{avg} \approx 30 \text{ ¢/KWh}$).

The results of both tests are represented in Fig 5, Fig.6.a, 6. b, and table 3. It can be seen by Fig.5 that both SOC trajectories are within the admissible limits, and all constraints are respected. Fig.6.a and b show that the deficit in power demand is covered by the utility grid at low pool price hours (0:00 till 6:00, and 22:00 till 24:00), whereas it is taken over by the battery, and the (DG) at high pool price hours. On the other hand, limiting the pollutant gas emissions weight, in simulation test 1, slightly impacts the total cost function. This can be verified through the excessive pollutant gas emissions in test 1 (49.6 Kg), and high operating hours of the (DG) (3.83 hours). Oppositely, by increasing this weight in simulation test 2, the total pollutant gas emissions are greatly alleviated (25.9 Kg), and so is the usage of (DG) (2 hours). The reduction in (DG) produced power is compensated by the utility grid which operating cost increases in simulation test 2 to 95.2\$ compared to 52.33 \$ in simulation test 1. Finally, by favoring the pollutant gas emissions goal over the operating cost, the total cost of the system is inconsiderably increased (a difference of 2.12\$ between two simulation tests). Hence, the applied (DP) doesn't compromise the objectives' achievement. In conclusion, the (DP) algorithm has a high convergence capability in multi-objective optimization problems and ensures the best tradeoff in achieving different predefined objectives.

V. CONCLUSION

In this paper, a multi-objective optimization problem is formulated and solved using the (DP) algorithm. The minimization of the total operating cost of the DC microgrid, and the reduction of the pollutant gas emissions are set as two independent objectives. To achieve these goals, a sole objective function is established, and weights are assigned to each of the predefined objectives. Several constraints, on operating units, are introduced to emulate a realistic microgrid model and scenario. To prove the viability of the (DP) algorithm in solving such optimization problem, and the effectiveness in achieving multi-objectives, two simulation

tests are conducted in which different weights are attributed to each of the fixed goals. Results show that (DP) converges in both simulations and find a feasible solution with respect to all defined constraints. Moreover, it offers to the user the option of goal's preference, through weights' selection, without compromising the optimality, and feasibility of the solution.

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