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Optimal Operation Management of a Microgrid Based on MOPSO and Differential Evolution Algorithms

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Abstract—**Local aggregation of Distributed Energy Resources (DERs), storage devices, controllable and uncontrollable loads is known as Microgrid. Microgrid operation management in order to reduce both cost and emission simultaneously is a very challenging task considering smart utilization of available energy resources in a highly constrained environment along with the conflicting nature of objectives. This paper aims to optimize the operation of an interconnected microgrid which comprises a variety of DERs and storage devices in order to minimize both cost and emission resulted from supplying local demands. Furthermore we will try to achieve an intelligent schedule to charge and discharge storage devices that provides the opportunity to benefit from market price fluctuations. The presented optimization framework is based on Multiobjective Particle Swarm Optimization (MOPSO) approach which adopts Differential Evolution (DE) algorithm to improve the search capability of the developed methodology. Finally results from an illustrative case study are provided and analyzed.**

Keywords-Differential Evolution; Microgrid; Multiobjective Particle Swarm Optimization; Pareto front.

I. INTRODUCTION

Local energy production is known as Distributed Generation. Along with the potential capability to provide reliable, efficient and secure electricity, Distributed Energy Resources (DERs) offer consumers and electric utilities many economical and environmental benefits. Local aggregation of distributed energy resources, storage devices, controllable and uncontrollable loads is known as Microgrid. Microgrids which are referred to as building blocks of the smart grids require a central management unit which monitors system status and makes the necessary decisions in order to optimize microgrid operation aligned with desired objectives while considering system constraints and regulatory rules [1]. In [2] the effects of utilizing a microgrid central controller to achieve a coordinate operation are investigated also [3] describes the role of a central controller which aims to optimize the operation of the microgrid by managing the production of local DGs and the amount of power to be exchanged with the upstream network. Minimization of the operating cost or in other words meeting the load demand in the most economic way is an important objective which has been seeking by researchers as [4]-[5] provide methods in order to reduce the operation cost of a microgrid containing battery storage. The algorithm proposed in [4] is based on particle swarm optimization while [5] utilizes a linear programming approach. In recent years, increased public awareness for the environmental effects of producing electricity, has led to devising new strategies in order to reduce emission beside other objectives in optimization scheme. In [6] a Mesh Adaptive Direct Search based methodology is proposed to determine an optimal operating strategy for minimizing microgrid's cost function taking into account the costs of emission as well as the operation cost.

This paper aims to optimize the operation of an interconnected microgrid which comprises a variety of DERs in order to minimize both cost and emission objectives simultaneously. Furthermore we will try to achieve an intelligent schedule to charge and discharge storage devices that provides the opportunity to benefit from market price fluctuations. Also in order to facilitate the process of decision making, microgrid central controller is provided with a set of optimal solutions to choose a suitable strategy based on desired preferences. The presented optimization framework is based on MOPSO approach which adopts Differential Evolution algorithm to improve the search capability of the developed methodology. In the procedure proposed in this paper emission factor of DG sources and upstream network are suitably incorporated into the model. Detailed modelling of storage devices' constraints along with utilizing realistic market prices and DG bids has made the methodology consistent with actual system conditions. The rest of paper is organized as follows. The problem formulation is presented in Section II. In Section III, a brief description of multiobjective optimization and MOPSO is provided. Simulation data and results are presented and discussed in Section IV. Finally the conclusion is given in Section V.

II. PROBLEM STATEMENT

A. *Objective Functions*

In this paper the objective of operation management of a microgrid is to minimize emitted pollutants and operation cost resulted from supplying local demands. However because of conflicting nature of these objectives, they cannot be minimized simultaneously. So our problem will be a highly constrained Multiobjective Optimization Problem. Decision variables involve DG units' production, energy to be requested from the main distribution grid and the amount of charging or discharging of storage devices during the specified period which should be effectively determined in order to achieve desired performance.

1) Minimization of Cost: The objective function for cost minimization can be written as

$$C(P)=\sum_{t=1}^{T}\left\{\sum_{i=1}^{N}B_i(P_{g_i}(t))+P_G(t)B_G(t)\right\} \quad (1)$$

In this equation P is a candidate solution in which $P_{gi}(t)$ and $P_G(t)$ are considered as real output power of ith generator and the purchased power from the main distribution grid at hour t respectively. N denotes the number of generating units in the microgrid and T shows the number of hours in optimization period. Also $B_G(t)$ refers to the energy price of main grid at tth hour and $B_i(P_{gi}(t))$ is the active-bid of ith unit for providing $P_{gi}(t)$ kilowatt output power, which is assumed to be as follows [3]

$$B_i(P_{g_i}(t))=b_iP_{g_i}(t)+c_i \quad (2)$$

2) Minimization of Emission: The amount of atmospheric pollutants such as carbon dioxide CO_2, sulphur oxide SO_x and nitrogen oxide NO_x caused by fossil-fuelled units either in microgrid or upstream network is considered in evaluating emission objective as follows

$$E(P)=\sum_{t=1}^{T}\left\{\sum_{k=1}^{M}\left\{\sum_{i=1}^{N}P_{g_i}(t)EF_{i,k}+P_G(t)EF_{G,k}(t)\right\}\right\} \quad (3)$$

In the above equation $EF_{i,k}$ and $EF_{G,k}$ represent the emission factor of the kth pollutant of the ith unit and upstream network in g/kWh during hour t respectively. Furthermore M shows the number of considered types of pollutants in the analysis.

B. Objective Constraints

1) Power balance constraint: According to this constraint the total generated power plus amount of energy purchased from the upstream network, should cover system's demand at each hour considering amount of charging/discharging of the battery bank in that hour.

$$\sum_{i=1}^{N}P_{g_i}(t)+P_G(t)=P_D(t)+P_B(t) \quad (4)$$

In which $P_D(t)$ denotes hourly demand and $P_B(t)$ represents amount of charging/discharging of the battery bank at tth hour which is considered positive as it is charging and negative during discharging periods. So during charging periods, demand would be increased as extra amount of energy is needed in order to charge batteries whereas in discharging time, demand decreases as a result of energy provided by batteries in that hour.

2) Generation Capacity Constraint: The real output power of each DG unit is constrained by its minimum and maximum production limits, i.e.,

$$P_{g_i}^{\min}\le P_{g_i}\le P_{g_i}^{\max} \quad (5)$$

For DGs that use renewable energy sources, upper bound will be their maximum available power at related hour.

3) Battery constraint: The battery bank which has been chosen from lead-acid type is utilized to store energy. Considering batteries in optimization plan will result in additional constraints which should be satisfied at all times. State of Charge (SOC) of the battery bank is calculated at each interval using following equation

$$\begin{aligned}SOC(t)&=SOC(t-1)(1-\delta(t))+\eta_{charge}\max(0,P_B(t))\Delta t\\&+\frac{1}{\eta_{discharge}}\min(0,P_B(t))\Delta t\end{aligned} \quad (6)$$

Where $SOC(t)$ and $SOC(t-1)$ denote amount of energy stored in the battery at hour t and $t\text{-}1$ respectively and δ represents self discharging coefficient. Also $\eta_{charge}/\eta_{discharge}$ is the battery charge/discharge efficiency during charging/discharging period. Δt is the time step which is assumed *1*h in this study. Battery state of charge is constrained by its lower and upper limits, i.e.,

$$SOC_{\min}\le SOC\le SOC_{\max} \quad (7)$$

Also there are other constraints that represent the maximum allowable energy taken or added to the battery is limited. This limitation is due to the maximum permissible charging/discharging current to be less than a specified percentage of the battery AH capacity [7], [8]. This constraint can be written as

$$|P_B(t)|\le P_b^{\max} \quad (8)$$

Initial SOC is assumed to be SOC_s as stated in following equation

$$SOC(t)\big|_{t=0}=SOC_s \quad (9)$$

Moreover an additional constraint regarding the battery ending state of charge is considered in this paper that ensures more than a specified percentage of the battery nominal capacity is stored at the end of desired time period. This can be shown as below

$$SOC(t)\big|_{t=T}\ge SOC_f \quad (10)$$

III. Multiobjective Optimization

Many real-world optimization problems involve simultaneous optimization of several conflicting objectives. A general multiobjective problem can be written as

$$\min_x f_i(x) \quad i=1,\dots,N_{obj} \quad (11)$$

$$subjected\ to:\begin{cases}g_j(x)=0 & j=1,\dots,r\\ h_k(x)\le 0 & k=1,\dots,z\end{cases} \quad (12)$$

Where f_i is the ith objective function, x is a candidate solution and N_{obj} shows the number of goals. Also r and z refer to the number of equality and inequality constraints respectively. The multiobjective optimization with conflicting objectives leads to a set of optimal solutions called non-dominated or Pareto optimal set, instead of one optimal solution [9].

A. Particle Swarm Optimization

Particle Swarm Optimization (PSO) was developed by Dr. Kennedy and Dr. Eberhart in 1995 [10], [11]. PSO is one of the most popular optimization algorithms, which was inspired by the swarm behavior to find the global optimal solution. In PSO, like any other evolutionary algorithm, individuals are initialized with random positions. Each potential solution, named a particle, is associated with a velocity vector which is dynamically adjusted using (13). The particles' position is then modified according to (14).

$$\begin{aligned} v_i^d(t+1) = w v_i^d(t) + c_1\, rand_1(pbest_i^d - x_i^d(t)) \\ + c_2\, rand_2(gbest^d - x_i^d(t)) \end{aligned} \tag{13}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{14}$$

In (13), $v_i^d(t)$ indicates the current velocity of the particle and w is known as inertia weight. Moreover c_1 and c_2 are learning coefficients which are used to control the step size towards personal best experience (pbest_i) and global best experience (gbest) respectively. Also $rand_1$ and $rand_2$ are two uniformly distributed random numbers within [0, 1] [12-13].

For extending the single objective optimization to a multiobjective one, it would be needed to redefine some of its components such as best local and global leader. Furthermore an external archive called *Repository* is required in order to store non-dominated solutions which are found during the search process.

B. Proposed Methodology

In this section the proposed algorithm will be further elaborated to form a methodology which is capable of handling the multiobjective problem at hand. In this paper Differential Evolution is used to improve exploration capability of the algorithm and prevent the search process from premature convergence. Generally the computational flow of the proposed MOPSO with the use of Differential Evolution can be described in the following steps:

Step1 (Initialization): First, the particles are initialized with random positions and velocities in the search space. The position of each particle can be initialized by randomly selecting a value over the dth search space dimension [x_d^{min}, x_d^{max}] with uniform probability and the same goes for initializing particles' velocity by limiting them to the range of [v_d^{min}, v_d^{max}] in order to prevent particles from going beyond the search space.

Step 2: In this step the objective values are evaluated for all particles in population and non-dominated particles are stored in repository. Then memory of each particle is initialized with its current position and keeps updating through process [14].

Step 3: While Itr_{max} has not been reached:

- Update each particle velocity and position in dth dimension using (13) and (14).
- Check feasibility of all individuals to make sure all constraints are met and maintain them in the search space in case particles go beyond their legal boundaries.
- Update local leader of each particle according to Pareto dominance concept.
- Update the non-dominated solutions set. Considering computational time, the size of archive should be limited to a predefined value. If archive size exceeds this value, truncate it by removing those individuals with the smallest normalized distance to other repository members so that stored positions properly cover trade-off surface.
- After updating the attained repository, DE is applied to the particles already exist in it according to the mutation operator of the DE/rand/1/bin strategy using (15)

$$V = X_{r1} + F(X_{r2} - X_{r3}) \tag{15}$$

  Where F is a real parameter called mutation constant and X_{r1}, X_{r2} and X_{r3} are three randomly selected members from the archive. Following the mutation stage, crossover and selection operators are applied to the V in order to form the trial vector and determine whether the target or trial vector survives to the next generation [15].

- Select the global leader to guide particles towards less crowded regions. In this paper a form of fitness sharing as proposed approach in [16] is incorporated which is based on the niching technique [17]. In the process, sharing distance d_{ij} is calculated for all individuals in the repository. Comparison of d_{ij} with the predefined niche radius σ_{share} gives the sharing function value as

$$sh(d_{ij}) = \begin{cases} 1 - (\dfrac{d_{ij}}{\sigma_{share}})^2 & if\ d_{ij} \le \sigma_{share} \\ 0 & otherwise \end{cases} \tag{16}$$

  Using the value of sharing function, a factor called niche count is determined for each individual. Then the fitness function which is in inverse proportion to the amount of the niche count can be evaluated for all particles. Finally roulette wheel selection is utilized to select the global best particle from the obtained repository [16].

- Update learning coefficients according to (17)-(19) in which w_{min} and w_{max} are the minimum and maximum values of w respectively. Moreover I_{max} shows the maximum number of iterations while I represnts the current iteration number.

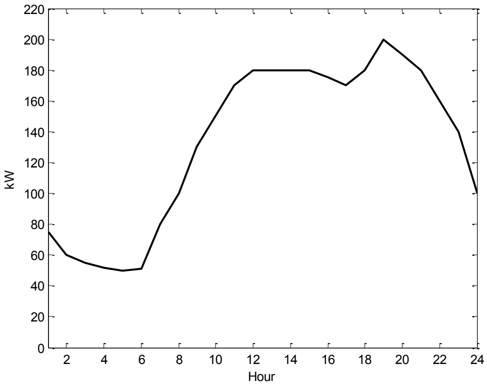

Figure 1. Daily Load Curve

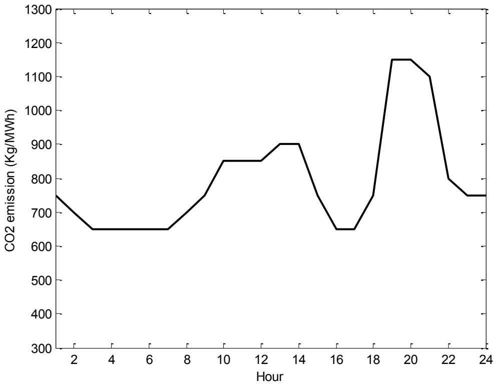

Figure 2. Typical 24-hour Emission Curve

TABLE I. INSTALLED DG SOURCES

Type	P_{min} (kW)	P_{max} (kW)	b_i (€ct/kWh)	c_i (€ct /h)	CO_2 (G/kWh)
MT	6	30	4.37	85.06	724.6
FC	3	30	2.84	255.18	489.4
WT	0	15	10.63	0	0
PV1	0	3	54.84	0	0
PV2	0	10	54.84	0	0

TABLE II. HOURLY ENERGY PRICES (€CT/KWH)

Hour	Price	Hour	Price	Hour	Price	Hour	Price
1	2.264	7	2.301	13	14.986	19	3.516
2	1.9	8	3.837	14	40	20	4.395
3	1.398	9	14.986	15	20.1	21	11.712
4	1.2	10	40	16	19.499	22	5.4
5	1.153	11	40	17	6	23	3
6	1.994	12	40	18	4.13	24	2.557

$$w = w_{\max} - (w_{\max} - w_{\min})\frac{I}{I_{\max}} \tag{17}$$

$$c_1 = (c_{1f} - c_{1i})\frac{I}{I_{\max}} + c_{1i} \tag{18}$$

$$c_2 = (c_{2f} - c_{2i})\frac{I}{I_{\max}} + c_{2i} \tag{19}$$

So the inertia weight keeps balancing between global and local search by linearly decreasing with the iterations. Furthermore (18)-(19) make c_1 to linearly decrease from its initial value to its final value and c_2 increases linearly to reach its final value in the last iteration.

- Increment iteration counter.

Step 4: End While

IV. NUMERICAL RESULTS

A. System Description

In this section a microgrid is considered for illustrating proposed model based on the data provided in [3]. The microgrid consists of one Microturbine (MT), one Fuel Cell (FC), one directly coupled Wind Turbine (WT) and two Photo Voltaic units (PVs). Minimum and maximum operating limits of the DG sources and related bid coefficients are given in TABLE I. Moreover we equipped the case study with a battery bank of size 40kWh, where SOC_{min} and SOC_{max} are set to 16kWh and 40kWh respectively and maximum charging and discharging capability of the battery bank is constrained by 4kW in each time step. Energy price data are given in TABLE II [3]. The load profile for a sample weekday is shown in Fig. 1 and Fig. 2 depicts a typical 24-hour emission curve of the upstream network [2]. Moreover normalized available power of the WT and PVs during the day is provided in Fig. 3.

B. Parameter Setting

The population size has been fixed to *2×D* where *D* is the dimension of solution space and w_{max} and w_{min} are set to 0.9 and 0.4 respectively. c_{1i}=2.5, c_{1f}=0.5, c_{2i}=0.5 and c_{2f}=2.5 are also assumed in this paper. For Niching technique, the value of σ_{share} is chosen 0.4.

C. Computational Results

The simulations were carried out starting from a base case (named case A) in which all system demand has to be supplied by the upstream network and neither DGs nor storage devices exist. Under these assumptions, an operating cost of €469.76 resulted while the total emission is 2650kg. To evaluate the influence of aggregating DG sources and storage devices under the coordination of a central microgrid management system, three sets of simulations are considered and compared with case A.

Case 1) Microgrid operation management for cost minimization

In this case it is assumed that microgrid central controller aims for optimal DG sources production, storage devices utilization and the amount of energy to be requested from the main grid in order to meet system demand in the most

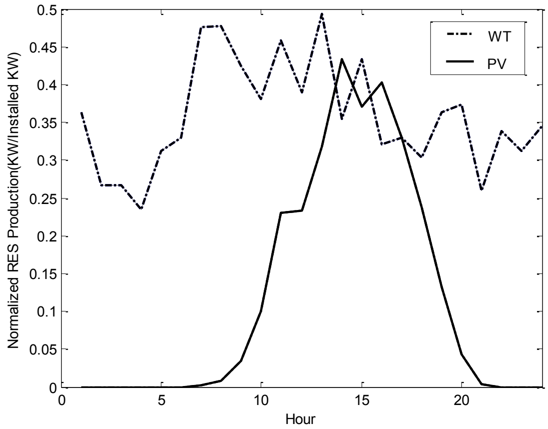

Figure 3. Normalized RES Hourly Production

TABLE III. SIMULATION RESULTS

Objective	Case 1	Case 2
Cost (€)	407.73	432.41
Emission (Kg)	2384.6	2233

economic way. Under this assumption total cost is €407.73 whereas 2384.6kg CO_2 is produced which show %13.2 and %10 reduction respectively in comparison with the base case (TABLE III). Daily scheduling is depicted in Fig. 4. For example during 10:00 when 150kWh is demanded by local loads (Fig. 1), 65.7kWh is supplied by local DGs and battery delivers 4kWh (-4kWh), the remainder energy (80.3kWh) is requested from the main grid to cover all demand. RES in the figures denotes the aggregation of total energy produced by renewable energy sources i.e., WT and PVs.

It is noticeable that during hours with lower market prices, it is preferred buying active power from the upstream network and charging batteries while during 9:00-15:00 that the market prices are substantially high, we can benefit from supplying loads by discharging the battery bank.

Case 2) Microgrid operation management for emission minimization

In this case the strategy with the lowest emission level is desired by the microgrid central controller. Obtained results are presented in TABLE III. As it can be seen in this case cost and emission are reduced by %8 and %15.7 respectively. It should be noted that in comparison with case 1, consumers are supplied with greener electricity in expense of more operating cost. Also according to the daily scheduling depicted in Fig. 5, in this case microgrid is more focused on local production so that the algorithm has set the output power of RESs to their maximum available power. It is also noticeable that batteries have been charged during hours with lower emission levels in order to improve grid's performance by providing their stored energy during hours with high emission levels.

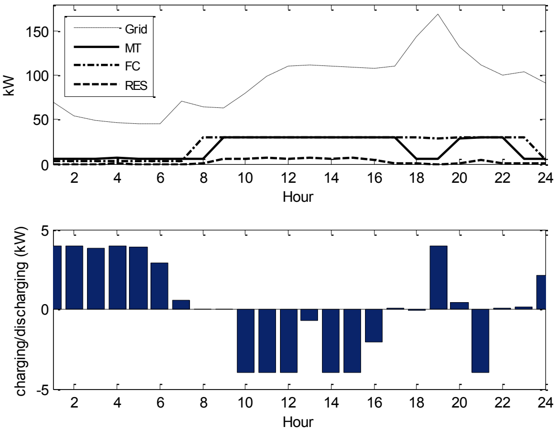

Figure 4. Daily Operation (Case 1)

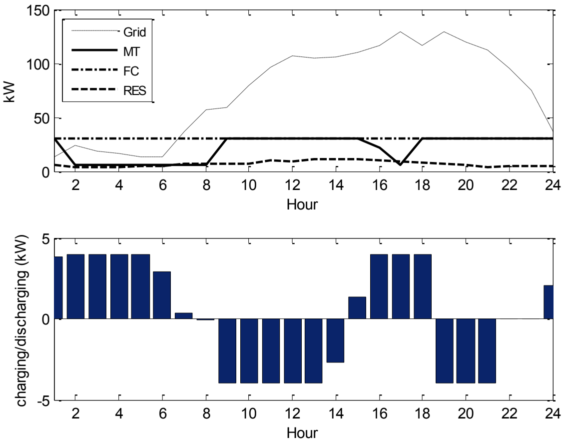

Figure 5. Daily Operation (Case 2)

Case 3) Microgrid operation management for cost and emission minimization simultaneously

In the previous cases, microgrid operation has been optimized in two extreme conditions, i.e., achieving the minimum cost or minimum environmental impact. In this case the problem is handled as a multiobjective optimization problem where both cost and emission are optimized simultaneously. Among most common multiobjective optimization approaches, a frequently used method is to combine all objectives to form a single function. In this method every objective according to its relative importance is weighted using a coefficient. The coefficients could be fixed at the beginning of optimization process or altered continuously in a range to reach the entire Pareto optimal set of solutions. It should be noted that in the former approach the preferences of the decision maker or relative importance of different goals must be specified in advance and in latter one in order to generate for instance 50 non-dominated solutions, it is required to apply the algorithm 50 times separately. However in a dynamic situation with lack of preference information, the desired strategy has to be selected from a pool of provided efficient solutions which have been obtained through an effective mechanism.

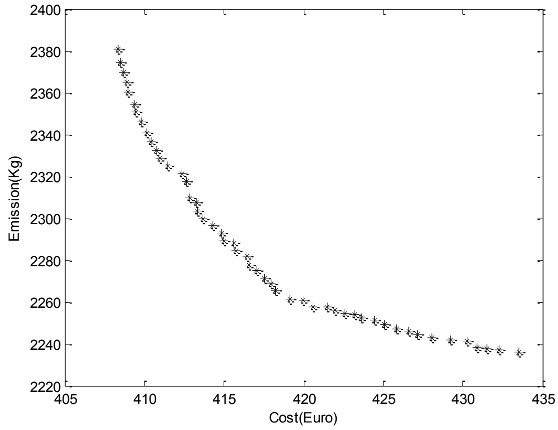

Figure 6. Optimal Pareto front

So to facilitate the process of decision making, microgrid central controller should be provided with the true Pareto front in order to increase the reliability of the decisions that have to be made [18]. Applying the proposed methodology on operation management problem in order to minimize cost and emission simultaneously, 50 non-dominated solutions that well cover the entire Pareto front of the problem have been obtained in a single run. Optimal Pareto front is depicted in Fig. 6. Results reveal that the proposed methodology preserves the diversity of non-dominated solutions over the trade-off surface so that the microgrid central controller can choose a suitable strategy based on desired preferences.

V. CONCLUSION

In this paper a methodology based on Multiobjective Particle Swarm Optimization and Differential Evolution algorithms has been presented for optimal operation management of a microgrid containing various kinds of distributed generation resources and storage devices. The problem has been formulated in multiobjective optimization framework with competing cost and emission goals in a highly constrained environment. Simulations were carried out for three different cases which show considerable improvements in the microgrid performance. Results show that the proposed approach is efficient for solving the multiobjective optimization problem of a microgrid and providing multiple Pareto optimal solutions in a single run, that well cover the entire Pareto front and preserves the diversity of non-dominated solutions over the trade-off surface. In addition it can be seen that aggregating multiple individual DGs and storage devices under the control of a central management unit, provides more opportunity and flexibility in utilizing available resources according to desired preferences. Furthermore it has been shown that an intelligent schedule to charge and discharge storage devices can lead to considerable reduction in cost and environmental impacts.

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