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Abstract— **In this paper, energy management problem of microgrids is formulated in the framework of non-linear multi-objective optimization problems. The goal is to develop an efficient strategy to supply the microgrids consumers with clean electricity in the most economical way. Moreover, in order to improve system performance and enhance energy efficiency, minimization of system losses is also considered in the optimization scheme. An efficient decision-making approach which adopts fuzzy adaptive particle swarm optimization algorithm is suggested to find the best compromise strategy. The proposed method has been applied to a typical microgrid comprises a variety of distributed energy resources and storage devices. Simulation results under different scenarios approve effectiveness of the proposed approach.**

Index Terms-- **Energy management system, Fuzzy systems, Microgrids, Particle swarm optimization, System losses.**

I. INTRODUCTION

Local aggregation of distributed energy resources (DERs), storage devices, controllable and uncontrollable loads is known as Microgrid (MG). Due to smaller size in comparison with the conventional large power systems and presence of more controllable elements, MGs allow a lot more flexibility to reach desired operation. Moreover, in MGs, supply and demand sides are aggregated in a smaller geographical area. As a result, power transmission lines and distribution feeders will be shortened which leads to substantial reduction in network losses. Reducing power dissipation not only lowers operational cost of the power system, but also helps to lessen the negative environmental impacts of producing electricity.

In recent years, because of the considerable technological developments and increasing orientation of utilities and consumers towards improving power system efficiency, massive studies have been done in the context of MGs. In [1], the functionality of a MG central controller is analyzed. The goal is to optimize the operation of a grid-connected MG which can participate in real-time electricity market. In [2], the problem is formulated as a multi-objective optimization problem with conflicting objectives of simultaneous cost and emission minimization. A hybrid fuzzy particle swarm optimization (PSO) algorithm is utilized to handle the problem. In [3], in order to reduce the communication overhead and make the energy management system (EMS) robust to failures, a distributed economic dispatch algorithm is proposed for a MG in grid-connected mode. In [4], a rolling horizon based energy management methodology is designed in which non-linearity of the model is dealt with piecewise linear models. In [5], mixed-integer linear programming approach along with model predictive control (MPC) is adopted in order to modeling and control of a MG considering operational constraints. The energy management problem of a three-phase, isolated MG is represented in [6]. Authors in [7] propose a PSO-based algorithm for operation management of a MG concerning for minimum operating cost of the system. The energy management problem of a residential MG containing both thermal and electrical subsystems is also considered in [8]. A sensitivity analysis is performed in order to verify performance of the proposed approach in case of imperfect information. In [9], an EMS based on multi-agent systems is proposed to optimal control of an integration of residential homes into a MG. In [10]-[11], chance-constrained MPC approach is adopted in EMS of multi-microgrid networks. In [12], cooperative operation of MGs is achieved through a joint probabilistic constraint which guarantees that the probability of not violating the power transaction limitation will be higher than a pre-specified confidence level.

Growing global concerns over serious shortage of fossil fuels and severe environmental pollution, in addition to consuming interest of the authorities in improving power system performance, highlight the importance of reducing system losses. In this paper, optimal power management problem of MGs is modeled as a non-linear multi-objective optimization problem. The goal is to minimize competing objectives of cost, emission and network losses. The multi-objective optimization problem is modeled as an interactive decision-making problem seeking a compromising strategy. Thus, the proposed model not only considers network loss in its formulation, but also develops an efficient strategy to optimize it. By considering system losses in optimization scheme, the MG central controller will face additional challenges due to the non-linear properties of loss dynamics. Confronting this difficulty, proposed interactive decision-making approach adopts fuzzy-PSO algorithm to reach the best compromise solution for the non-linear multi-objective optimization problem at hand. The rest of paper is organized

as follows. The optimization problem is summarized in section II. The proposed decision-making approach and fuzzy-PSO algorithm are introduced in sections III and IV, respectively. In section V, an illustrative case study is analyzed under several scenarios. Finally, concluding remarks are given in section VI.

II. PROBLEM STATEMENT

In this paper, operation management problem of MGs is considered as a non-linear constrained multi-objective optimization problem. Decision variables contain DGs production, level of energy to be requested from the main grid and the hourly amount of charging/discharging of storage devices during the optimization horizon.

A. Objective Functions

Cost minimization: MG total cost is resulted from local DGs production in addition to the cost of purchasing power from the main grid as given below.

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

$$B_i (P_{g,i}(t)) = b_i P_{g,i}(t) + c_i \quad (2)$$

In (1), T denotes the length of adopted optimization period while N shows the number of micro-sources in the MG. Moreover, P is considered as a vector including hourly production of local units ($P_{g,i}(t)$) and purchased power from the main grid ($P_G(t)$). Furthermore, $B_i(P_{g,i}(t))$ is bid of the ith DG unit which is assumed to be a linear function of units production according to (2). Where, b_i represents the variable cost and c_i is the fixed cost of the ith unit [1]. $B_G(t)$ denotes the price of purchasing one kilowatt hour energy from the main grid.

Environmental impact minimization: The total emission of a MG can be approximately calculated as follows.

$$E(P) = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N} P_{g,i}(t) EF_i + P_G(t) EF_G(t) \right\} \quad (3)$$

In (3), EF_i represents emission factor of the ith unit in the MG and $EF_G(t)$ shows the same factor for the upstream network at t^{th} hour in *gr/kWh*. Since RESs do not have environmental impacts, they are not considered in evaluating total emission i.e., related emission factors in (3) are set to zero. In general, extracting an emission curve for the upstream network is a really challenging task which requires the composition of generation resources. According to [13], while the penetration of MGs is relatively low, the initial unit commitment of the upstream network will not change. So, in order to analyze the impact of MGs on environmental characteristics, a short-term prediction of emission curve for the grid could be derived.

System loss minimization: Network losses depend on the voltages and currents of the system. In this paper, system losses are calculated based on the network power flow using Power System Simulation Package (MATPOWER). System loss could be computed after the power flow problem is solved. For power flow calculations, the point of common coupling (i.e., where the MG is connected to the main grid) is considered as the slack bus. The nodal bus injections are determined according to the load demands and generators injections. For any specified pattern of load and generation, the power flow problem is solved and line losses are directly calculated [14]. In this study, it is assumed that required reactive power is provided through local compensators thus all distributed generators produce active power at unity power factor. Accordingly, reactive power dispatch is not considered in this study.

B. Problem Constraints

Power balance constraint: Following equation shows the power balance constraint. Where, $P_D(t)$ and $P_L(t)$ represent local demand and system loss at hour t, respectively. In addition, $P_{Batt}(t)$ indicates charging/ discharging power of storage devices at the tth hour which is assumed to be positive/negative during charging/discharging periods.

$$\sum_{i=1}^{N} P_{g,i}(t) + P_G(t) = P_D(t) + P_{Batt}(t) + P_L(t) \quad (4)$$

Generation capacity constraint: For normal system operation, the real output power of each generation unit is limited to its lower and upper permissible values (see (5)).

$$P_{g,i}^{\min} \leq P_{g,i} \leq P_{g,i}^{\max} \quad (5)$$

Battery constrains: Using the same variable for both charging and discharging powers ($P_{Batt}(t)$), the evolution of state of charge (SOC) of a battery can be described by the following dynamical equation where $SOC(t)$ and $SOC(t-1)$ denote amount of energy in *kWh* that are stored in the battery at successive hours of t and $t-1$, respectively [15]. Moreover, $\eta_{charge}/\eta_{discharge}$ shows the battery charging/discharging efficiency.

$$SOC(t) = SOC(t-1) + \eta_{charge} \max(0, P_{Batt}(t))$$
$$+ \frac{1}{\eta_{discharge}} \min(0, P_{Batt}(t)) \quad (6)$$

In order for safe battery operation, $SOC(t)$ should be constrained to its lower and upper limits according to (7). Referring to (8), due to the limitation of charging/discharging current of the batteries, maximum charging/discharging power ($P_{B,Max}$) should be limited to the permissible value.

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

$$|P_{Batt}(t)| \leq P_{B,\max} \quad (8)$$

III. MULTI-OBJECTIVE OPTIMIZATION

In a multi-objective optimization problem, several conflicting objective functions should be optimized simultaneously. In this paper, it is proposed that through making compromise between involved objectives, decision-maker could arrive at a Pareto optimal solution which optimizes the problem from all objectives point of view. The multi-objective problem is modeled as an interactive decision-

making process seeking a compromising strategy satisfying all the objectives. Accordingly, in order to model the multi-objective optimization problem at hand, an interactive objective function $B(X)$ is incorporated as follows:

$$Max \quad B(X) = \prod_{i=1}^{N_{obj}} [f_{i,max} - f_i(X)] \tag{9}$$

In (9), f_i is the ith objective function to be minimized, where $f_{i,max}$ shows the worst value of that. The symbol Π indicates the product operation. Maximization of the objective function in the form of (9), insures maximization of the product of each objective function distance from its related worst value. Generally, normalization of objective function is preferred. This way, the optimal solution will not be affected by the objective functions magnitudes [16]. So, the objective function is modified according to (10) in which F_{ni} indicates the normalized value calculated using (11).

$$Max \quad S = \prod_{i=1}^{N_{obj}} (1 - F_{ni})^{\lambda_i} \tag{10}$$

$$F_{ni} = \frac{f_i - f_{i,min}}{f_{i,max} - f_{i,min}} \tag{11}$$

In (11), $f_{i,min}$ and $f_{i,max}$ show the minimum and maximum values of the ith objective function, respectively. Moreover, λ_i in (10) refers to the relative importance of each objective function. In this paper, in order to insure that interactive optimization procedure starts from an acceptable point, a penalty term is considered in the objective function as equation (12) in which M is a large positive coefficient. The resulting optimization problem is a high-dimensional non-linear problem subjected to a large number of constraints which is very difficult to solve with ordinary optimization approaches. In this paper, in order to find the optimal solution of the proposed optimization problem, fuzzy-PSO method is adopted.

$$Max \quad F = S - M \times \sum_{i=1}^{N_{obj}} \max(0, -\text{sign}(1 - F_{ni})) \tag{12}$$

IV. FUZZY PARTICLE SWARM OPTIMIZATION

In PSO, a population of potential solutions called particles explore the multi-dimensional search space to find the global optimum solution. In the process, each particle is associated with two vectors which indicate particle velocity and position. Referring to (13), the velocity vector of each particle keeps updating through the search process according to the best experience of its own (*pbest*) and other particles (*gbest*). Accordingly, particle position vector is adjusted using (14). In (13), parameter w which is known as inertia weight is used to make balance between exploration and exploitation and generally takes values in the range of [0.4-1]. Moreover, c_1 and c_2 are called acceleration coefficients usually within [1-2] while r_1 and r_2 are random numbers in the range of [0-1].

$$v_i^d(t) = w v_i^d(t-1) + c_1 r_1 (\text{pbest}_i^d(t-1) - x_i^d(t-1))$$
$$+ c_2 r_2 (\text{gbest}^d(t-1) - x_i^d(t-1)) \tag{13}$$

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

In PSO, the algorithm performance is heavily dependent on the value of inertia weight [17]-[18]. Because of the complexity of searching process, finding an exact mathematical model in order to adjust these parameters is a difficult task. A common way to adjust the value of inertia weight is using the linear equation represented in (15). In this equation, Itr_{max} shows the maximum number of iterations while Itr is the current iteration number. Moreover, w_{max} and w_{min} denote maximum and minimum values of inertia weight, respectively. As the value of inertia weight varies with time, we call this algorithm time varying PSO (TVPSO) in the following.

$$w(Itr) = w_{max} - (w_{max} - w_{min}) \frac{Itr}{Itr_{max}} \tag{15}$$

In this paper, according to [17], a fuzzy system for dynamically adaptation of inertia weight is proposed (FPSO). Two inputs of the fuzzy system are the current normalized best performance (NF) (see (16)) and the current inertia weight while the correction of the inertia weight (Δw) according to the (17) is considered as the output.

$$NF = 1 - \prod_{i=1}^{N_{obj}} (1 - F_{ni})^{\lambda_i} \tag{16}$$

$$w(t+1) = w(t) + \Delta w \tag{17}$$

Table I shows the nine fuzzy rules applied to the system. In this table, "L", "M" and "H" stand for low, medium and high, respectively. Also, Δw can be negative (N), zero (Z) or positive (P). All the membership functions are considered triangular as shown in Fig. 1 according to the information presented in [17]-[18].
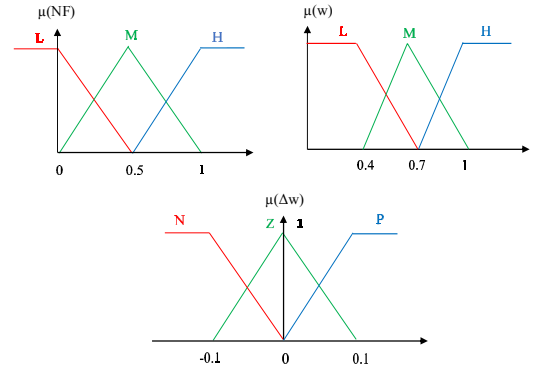
Figure 1. Membership functions of NF, w, Δw

TABLE I.   FUZZY RULES

Rule no.	NF	W	Δw	Rule no.	NF	W	Δw
1	L	L	Z	6	M	H	N
2	L	M	N	7	H	L	P
3	L	H	N	8	H	M	Z
4	M	L	P	9	H	H	N
5	M	M	Z				

V. CASE STUDY

In this section, the proposed approach is illustrated through a typical case study presented in [1] and [15] (see Fig. 2). It is assumed that the MG is equipped with a 40kWh battery bank with the $P_{b,max}$=4kW that works in the range of 20% to 85% of its nominal capacity. Moreover, $SOC_{initial}$ is set to 60% of SOC_{max}. The analysis has been done in a day with 3188 kWh energy demand. The hourly load curve and the normalized estimated available power of wind turbine (WT) and photovoltaic systems (PVs) during the day can be found in Fig. 3. Operating limits of the DG sources, the bid coefficients assumed in the model and emission data for the fuel consuming units are represented in Table II. Data related to the resistance and reactance of the lines and typical 24-hour emission data can be found in [1] and [13], respectively. Moreover, the real-time market energy prices are given in Table III. It is assumed that the RESs (WT & PVs) are non-dispatchable resources.
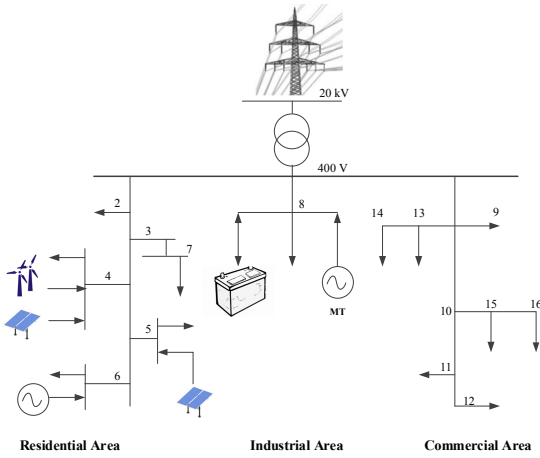

Figure 2. A typical LV microgrid

TABLE II. INSTALLED DG SOURCES [1], [13]

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

MT: Microturbine, FC: Fuel cell

Scenario A) Base scenario. In this scenario all system demand has to be supplied through the main grid, i.e., neither DGs nor storage devices exist. Total operation cost in this scenario is equal to 498 € while 2793 kg emission and 165.55 kW power losses is incurred to the system. According to this results, the amounts of three objectives are substantially high in this scenario. To evaluate the influence of aggregating DG sources and storage devices under the coordination of a central control unit and effectiveness of the proposed approach, different scenarios are considered and simulation results are compared with the base scenario.

TABLE III. REAL-TIME MARKET ENERGY PRICES (€/KWH) [1]

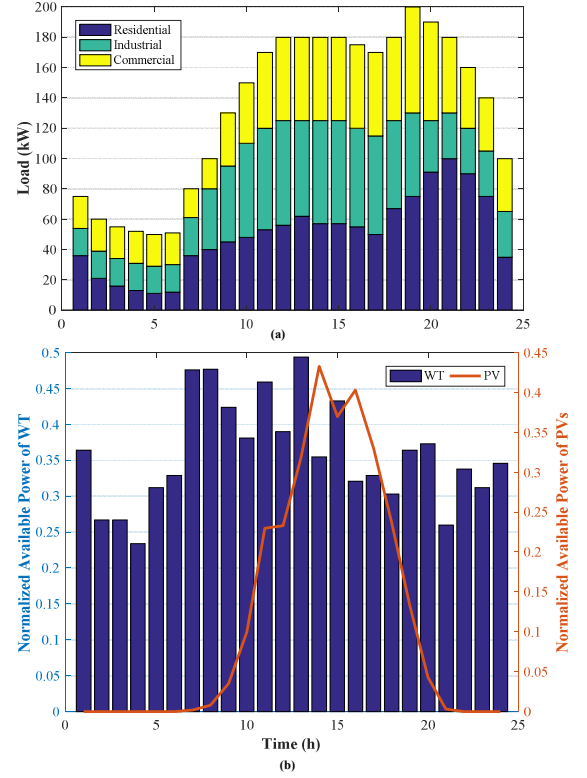| t	Price	T	Price	t	Price	t	Price
1	2.264	7	2.301	13	14.986	19	3.516
2	1.900	8	3.837	14	40.000	20	4.395
3	1.398	9	14.986	15	20.100	21	11.712
4	1.200	10	40.000	16	19.499	22	5.400
5	1.153	11	40.000	17	6.000	23	3.000
6	1.994	12	40.000	18	4.130	24	2.557

Figure 3. Daily load curve (a), Normalized estimated power outputs from WT and PVs (b) [1]

Scenario B) Microgrid operation management in presence of energy storage devices. In this scenario, optimal operating strategy of a MG which is equipped with a battery bank is devised in three different cases named Case 1 to 3. Simulation results for 10 random trials are presented in Table IV and Table V. In the following, obtained results in each case will be discussed.

Case 1) Cost minimization: In this case, it is assumed that MG central controller tries to achieve the optimal strategy in order to meet system demand in the most economical way. From Table V it can be seen that total cost resulted from supplying local demand has been reduced by 11.61% in comparison with the base scenario and a substantial reduction has been made in network losses. Due to space limitation, daily scheduling and battery charging/discharging process of this case are exemplary shown in Fig. 4. It is noticeable that during hours with lower market prices, it is preferred to request active power from the upstream network (see Fig. 5) and charge batteries while during the hours with high market prices, DGs output is set to their maximum values. In latter case, an important part of loads is supplied by discharging the energy stored in the battery. Obviously, storing capability

provides the MG with the opportunity to benefit considerably from market price fluctuations.

Case 2) Environmental impacts minimization: In this case, the optimal strategy which results in lowest environmental impacts is followed by the MG. According to Table V, in comparison with the base scenario, 17.25% reduction in the produced emission level has been reached. Moreover, as a result of more relying on RESs which are geographically located closer to loads in comparison to the upstream network, a 46% reduction in network losses has been also achieved. Comparing with the previous case, it is obvious that in this case consumers are supplied with greener electricity at the expense of more operation cost.

Case 3) Loss minimization: In this case, it is assumed that the central controller aims to optimize the MG operation in a way that total loss resulted from supplying local loads is minimized. Simulation results are given in Table V. It can be seen that in this case total loss has reached its minimum value, so that in comparison with the base scenario, a reduction of 48% has been made. As a result of more relying on local production, the geographical distance between production and consumption could be reduced and a considerable reduction in network loss could be achieved. Optimal requested power from the upstream network in all three cases along with the base scenario, are shown in Fig. 5. As it can be seen, through aggregating local production and consumption in a MG framework, the reliance of loads on the main grid has been noticeably reduced.

Scenario C) Simultaneous minimization of cost, emission and loss. In this scenario, it is assumed that central controller is faced with a non-linear multi-objective optimization problem with three conflicting objectives including cost, emission and system losses. Simulation results are shown in Table VI. From the Table VI, it can be seen that in the best compromise solution, values of all three objectives are satisfactory in comparison with their extreme values extracted from scenario *B*. It is important to mention that by considering network losses as an objective in optimization problem, total loss can be desirably reduced through accepting slight increase in system operational cost which shows efficient interaction among conflicting objectives. The convergence characteristics of the optimization process is shown in Fig. 6 in which three different approaches for adjusting the value of inertia weight are compared. In the standard PSO, the value of w is fixed to 0.9 while in TVPSO using (15) the weight is linearly decreasing from 0.9 to 0.4. As illustrated in the Fig. 6, performance obtained by the FPSO method outweighs the ones from other algorithms in finding the best compromise solution which approves its capability in solving non-linear complex problems.

TABLE IV. OBJECTIVES EVALUATIONS FOR 10 TRIALS (SCENARIO B)

Case	Best	Worst	Average	SD
Case 1: Cost minimization (€)	440.15	441.85	440.65	0.47
Case 2: Emission minimization (kg)	2310.9	2315.5	2313.72	1.43
Case 3: Loss minimization (kW)	86.04	86.30	86.12	0.08

SD: Standard deviation

TABLE V. RESULTS COMPARISON OF CASES 1, 2 AND 3

Case	P_G (kW)	PMG (kW)	Cost (€)	Emission (kg)	Loss (kW)
Case 1	2156	1121	440.15	2372.30	93.63
Case 2	1791	1484	448.75	2310.90	89.47
Case 3	1858	1416	448.23	2357.20	86.04

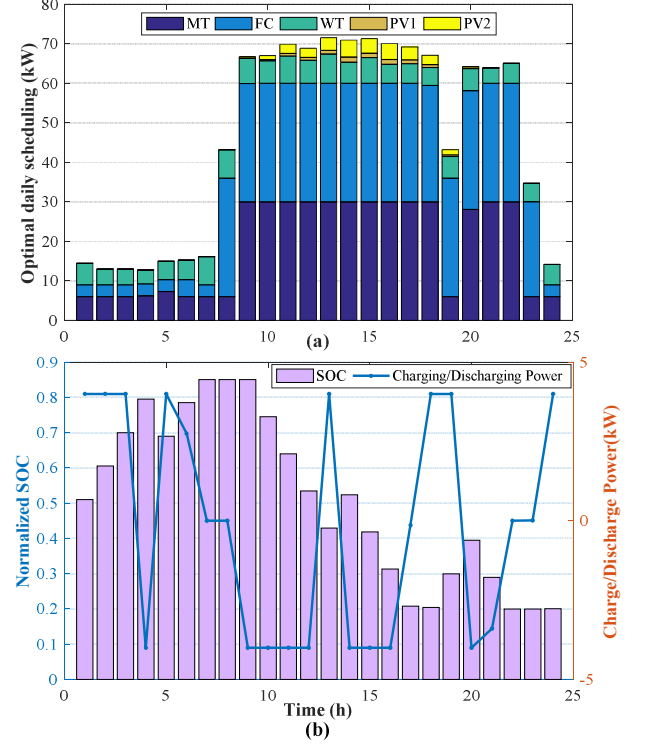PMG (kW): Total generated power of microgrid

Figure 4. Optimal daily scheduling of DGs (a) and Battery profile (b) in the case of Cost minimization, Scenario B
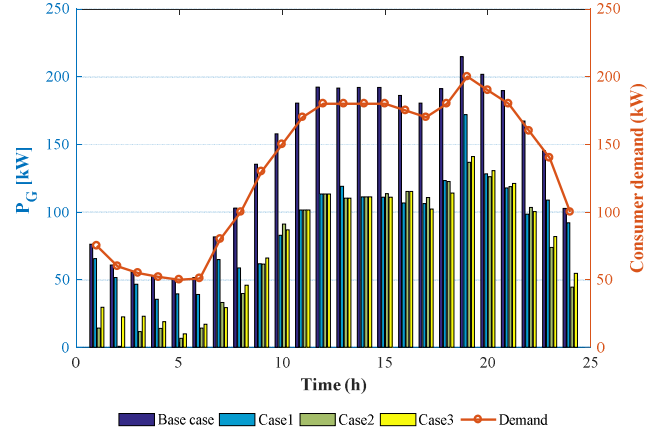

Figure 5. Optimal requested power from the utility (Scenario B)

VI. CONCLUSION

In this paper, optimal operation management problem of a microgrid was modeled as a non-linear constrained multi-objective maximization problem. The proposed model not only considers network losses in its formulation, but also develops an optimal strategy to efficiently optimize it.

Moreover, a hybrid decision-making approach which adopts fuzzy-PSO algorithm was introduced as a solution approach. Utilizing proposed approach, the compromise strategy can be extracted through efficient interaction among conflicting objectives. Finally, effectiveness of the proposed approach was evaluated under several scenarios.

TABLE VI. OPTIMAL DAILY SCHEDULING FOR THE BEST COMPROMISE SOLUTION (COST: 444.78 €, EMISSION: 2323.7 KG, LOSS: 87.65 KW)

| T	SOC	C/D	WT	PV1	PV2	MT	FC	Grid
1	20.4	4.0	5.5	0.0	0.0	30.0	28.5	15.7
2	24.2	4.0	4.0	0.0	0.0	20.5	8.2	21.8
3	28.0	4.0	4.0	0.0	0.0	6.0	15.7	33.9
4	31.8	2.3	3.5	0.0	0.0	8.7	18.7	24.0
5	34.0	0.0	4.7	0.0	0.0	6.3	3.0	36.0
6	34.0	-4.0	4.9	0.0	0.0	6.0	3.0	33.5
7	29.8	4.0	7.0	0.0	0.0	14.8	30.0	33.0
8	33.6	-4.0	7.2	0.0	0.1	30.0	30.0	30.0
9	29.4	4.0	6.4	0.1	0.4	30.0	30.0	69.9
10	33.2	-4.0	5.7	0.3	1.0	30.0	30.0	82.8
11	29.0	-4.0	6.9	0.7	2.3	30.0	30.0	101.5
12	24.8	-4.0	5.9	0.7	2.3	30.0	30.0	113.5
13	20.6	-4.0	7.4	1.0	3.2	30.0	30.0	110.3
14	16.3	-4.0	5.3	1.3	4.3	30.0	30.0	111.3
15	12.1	-3.9	6.5	1.1	3.7	30.0	30.0	111.0
16	8.0	4.0	4.8	1.2	4.0	30.0	29.4	115.9
17	11.8	4.0	4.9	1.0	3.3	30.0	30.0	110.8
18	15.6	4.0	4.6	0.7	2.4	30.0	30.0	122.6
19	19.4	-4.0	5.5	0.4	1.3	30.0	30.0	136.8
20	15.2	-4.0	5.6	0.1	0.4	30.0	30.0	126.2
21	11.0	-2.8	3.9	0.0	0.0	30.0	30.0	118.4
22	8.0	4.0	5.1	0.0	0.0	30.0	30.0	102.7
23	11.8	-3.6	4.7	0.0	0.0	29.7	30.0	74.4
24	8.0	4.0	5.2	0.0	0.0	30.0	30.0	40.3
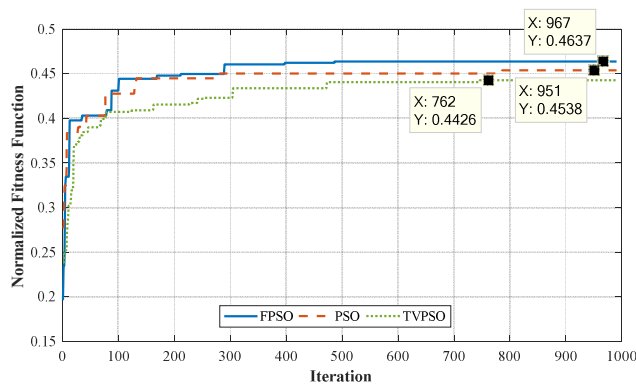
Figure 6. Convergence analysis (scenario C)

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