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Energy Management in a Micro-Grid with High Penetration of Renewable Resources Considering Emission Constraints

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Abstract— In recent years, renewable energies have become one of the most important sources of electrical energy. Their social and environmental benefits as well as economic issues result in further utilization of these energy resources. Moreover, it has become a challenging task for many modern utilities and energy management systems to derive an optimal operational plan for better utilization of renewable resources of energy regarding to different objectives. In this paper, a Modified Particle Swarm Optimization (MPSO) algorithm based on a fuzzy self-adaptive mechanism is utilized and implemented to solve the energy management problem in a typical micro-grid considering cost and emission as objectives. The algorithm is tested via several scenarios and its superior performance is compared to those from other multi-objective evolutionary algorithms such as Non-dominated Sorting Genetic Algorithm (NSGA II) and standard PSO.

Keywords— Energy management, micro-grid, particle swarm optimization, fuzzy self adaptive mechanism.

I. INTRODUCTION

Nowadays as a result of the rapid socioeconomic growth and environmental concerns, higher service reliability, better power quality, increased energy efficiency and energy independency, exploring alternative energy resources, especially the renewable ones, has become the field of interests for many modern societies. In this regard, Micro-Grid (MG) which is comprised of various alternative energy sources can serve as a basic tool to reach the desired objectives while distributing electricity more effectively, economically and securely [1-3]. Besides, it seems that energy management systems and power system optimizers accompanied by integration of new generation resources which form a whole micro-grid vision, have the capability of serving as a basic tool to reach energy independence and climate changes objectives. Additionally, with low incorporation of renewable energy sources the total effect on grid operation is confined, but as their penetrations are augmented their mutual effects increase too [4-6]. Regarding

all the previous mentioned points, it can be easily concluded that there is a strong need for more precise scheduling of energy sources in a micro-grid which is helpful for its optimal operation and better behavior both in economy and emission.

Generally, most previous optimization algorithms and optimal power dispatch programs dealt with the case of single objective. These algorithms were faced with the problem of deciding the most economical units to dispatch. For example [7] proposes a hierarchical approach for economic dispatch while considering risk management in the power market. Reference [8] proposes a linear programming based optimization procedure where one objective is considered at any time. Reference [9] also develops a Revised Adaptive Hopfield Neural Network (RAHNN) scheme to deal with this problem. Likewise, evolutionary programming techniques have been applied to solve such kind of problems.

Nowadays, various optimization techniques are implemented to handle the optimal operation management problem in a more efficient way. As examples, optimal design methodologies under the carbon emission using meta-heuristic techniques are proposed in [10]. Different multi-objective evolutionary approaches are also reported in articles for optimal power dispatching [11-17]. Among the previous mentioned optimization methods, PSO has been significantly used in optimal operation management problem mainly due to its population-based search capability as well as simplicity, convergence speed, and robustness, in spite of the performance of a conventional PSO algorithm greatly depends upon its learning and weighting factors and it may be faced to the problem of being trapped in local optima.

In this paper, a fuzzy self adaptive particle swarm optimization algorithm is utilized and implemented to solve the energy management problem inside a typical micro-grid with high penetration of renewable resources considering economy and emission as competitive objectives. Since the two objectives are not the same, instead of a single solution, a Pareto front of optimal solutions is obtained for the mentioned problem, which is stored in a finite-sized repository. The

feasibility of the proposed method is also tested in a micro-grid with five DG units and its performance is compared with those from standard PSO and NSGA II.

II. FORMULATION OF ENERGY MANAGEMENT PROBLEM

The optimal economic/emission power dispatch and energy management problem in a typical micro-grid can be formulated as a multi-objective optimization model as follows:

A. Objective Functions

• Objective 1: Cost Minimization

The first objective function can be formulated as below:

$$\begin{aligned} \text{Min } f_1(X) &= \sum_{t=1}^T \text{Cost}^t \\ &= \sum_{t=1}^T \left\{ \sum_{i=1}^{N_g} [u_i(t) P_{Gi}(t) B_{Gi}(t) + S_{Gi} |u_i(t) - u_i(t-1)|] \right. \\ &\quad \left. + \sum_{j=1}^{N_s} [u_j(t) P_{sj}(t) B_{sj}(t) + S_{sj} |u_j(t) - u_j(t-1)|] + P_{Grid}(t) B_{Grid}(t) \right\} \end{aligned} \quad (1)$$

where $B_{Gi}(t)$ and $B_{sj}(t)$ are the bids of the DG sources and storage options at hour t . S_{Gi} and S_{sj} are the start-up or shut-down costs for the i^{th} DG and the j^{th} storage device, respectively. $P_{Grid}(t)$ is the active power, which is bought (sold) from (to) the utility at time t and $B_{Grid}(t)$ is the bid of utility at t . X is the vector of state variables which includes active powers of units and their related ON or OFF states.

• Objective 2: Pollutants Emissions Minimization

To consider the environmental effect of pollutants emissions as the second objective, three of the most important emissions are involved in the optimization problem: Carbon dioxide (CO₂) Sulfur dioxide (SO₂) and Nitrogen oxides (NO_x):

$$\begin{aligned} \text{Min } f_2(X) &= \sum_{t=1}^T \text{Emission}^t \\ &= \sum_{t=1}^T \left\{ \sum_{i=1}^{N_g} [u_i(t) P_{Gi}(t) E_{Gi}(t)] + \sum_{j=1}^{N_s} [u_j(t) P_{sj}(t) E_{sj}(t)] \right. \\ &\quad \left. + P_{Grid}(t) E_{Grid}(t) \right\} \end{aligned} \quad (2)$$

where all the above parameters are defined as before and $E_{Gi}(t)$, $E_{sj}(t)$ and $E_{Grid}(t)$ are described as the amount of total emissions in kg/MWh for each DG, storage unit and the utility at hour t , respectively.

B. Constraints

• Load balance:

$$\sum_{i=1}^{N_g} P_{Gi}(t) + \sum_{j=1}^{N_s} P_{sj}(t) + P_{Grid}(t) = \sum_{k=1}^{N_k} P_{Lk}(t) \quad (3)$$

where P_{Lk} is the amount of the k^{th} load and N_k is the total number of load levels.

• Active power constraints of units:

$$P_{Gi,\min}(t) \leq P_{Gi}(t) \leq P_{Gi,\max}(t) \quad (4)$$

$$P_{sj,\min}(t) \leq P_{sj}(t) \leq P_{sj,\max}(t)$$

$$P_{grid,\min}(t) \leq P_{Grid}(t) \leq P_{grid,\max}(t)$$

where $P_{G,\min}(t)$, $P_{s,\min}(t)$ and $P_{grid,\min}(t)$ are the minimum active powers of the i^{th} DG, the j^{th} storage and the utility at time t . In a similar manner, $P_{G,\max}(t)$, $P_{s,\max}(t)$ and $P_{grid,\max}(t)$ are the maximum power productions of corresponding units at hour t .

• Charge/Discharge rate limits of storage devices:

Due to limitation on charge and discharge rate of storage devices during each time interval, the following equation and constraint can be written:

$$SoC_{sj}(t) = SoC_{sj}(t-1) + P_{Chg/Dchg_j}(t) \quad (5)$$

$$0 \leq |P_{Chg/Dchg_j}(t)| \leq P_{CDSj,\max} \quad (6)$$

where $SoC_{sj}(t)$ and $SoC_{sj}(t-1)$ are the amounts of storage state of charge at hour t and $t-1$ respectively, $P_{Chg/Dchg_j}(t)$ is the amount of charge(discharge) during hour t and $P_{CDSj,\max}$ is the maximum rate of charge or discharge during each time interval.

III. COMPONENTS OF SAMPLE MICRO-GRID

In this paper, a typical L.V. micro-grid has been considered as a benchmark for testing the proficiency of the proposed algorithms. As shown in Fig. 1, the micro-grid includes various types of DGs such as micro turbine (MT), fuel cell (FC), photovoltaic (PV), wind turbine (WT) and storage devices like Nickel-Metal-Hydrate (NiMH) battery. It is assumed that all DG sources produce active power at unity power factor, neither requesting nor producing reactive power. There is also a power exchange link between the mentioned micro-grid and the utility (L.V. network) used for energy trading during different hours of a day based on decisions made by micro-grid central controller (μ_{CC}).

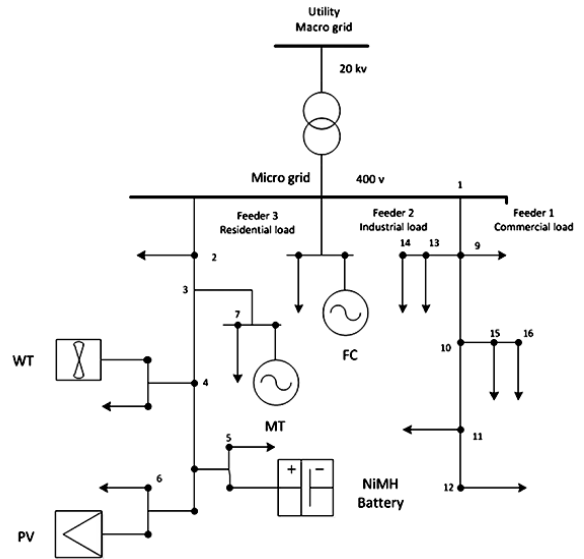


Fig. 1. A typical L.V. micro-grid model

IV. MULTI-OBJECTIVE OPTIMIZATION

Generally, in a multi-objective optimization problem, there are different objective functions required to be optimized simultaneously considering a set of equality and inequality constraints as follows:

$$\begin{aligned} &\text{Minimize } F = [f_1(X), f_2(X), \dots, f_n(X)]^T \\ &\text{Subject to: } \begin{cases} g_i(X) < 0 & i = 1, 2, \dots, N_{ueq} \\ h_i(X) = 0 & i = 1, 2, \dots, N_{eq} \end{cases} \end{aligned} \quad (7)$$

where F is a vector including objective functions and X is the vector of the optimization variables, $f_i(X)$ is the i^{th} objective function, $g_i(X)$ and $h_i(X)$ are the equality and inequality constraints respectively and n is the number of objective functions. In this regard, if X and Y are considered as two of the optimal solutions for a given multi-objective problem, then one dominates the other or none dominates each other i.e., a solution X dominates Y and it's called a non-dominated solution if the following two conditions are satisfied:

$$\begin{aligned} &\forall j \in \{1, 2, \dots, n\}, f_j(X) \leq f_j(Y) \\ &\exists k \in \{1, 2, \dots, n\}, f_k(X) < f_k(Y) \end{aligned} \quad (8)$$

Through the entire search space, the non-dominated solutions are considered as "Pareto-optimal" and form the Pareto-optimal set or Pareto-optimal front. Likewise, "Pareto-dominance" is a concept used for determining the eligibility of each particle (or solution) to be stored in the repository of non-dominated solutions.

V. PARTICLE SWARM OPTIMIZATION (PSO)

To reach the optimal point in a search space using a typical PSO algorithm, particles must update their next displacements according to their own velocities, their best performances ($P_{best,i}$) and the best performances of their best informant (G_{best}) as formulated below:

$$V_i^{(k+1)} = \omega \times V_i^{(k)} + C_1 \times \alpha \times (P_{best,i} - X_i^{(k)}) + C_2 \times \beta \times (G_{best} - X_i^{(k)}) \quad (9)$$

$$X_i^{(k+1)} = X_i^{(k)} + V_i^{(k+1)} \quad (10)$$

where $V_i^{(k+1)}$ and $X_i^{(k+1)}$ are the updated velocity and position vectors of the i^{th} particle based on the three displacement fundamentals, α and β denote two random numbers in the range $[0,1]$, C_1 and C_2 are the learning factors and ω refers to inertia or momentum weight factor.

A. Modified PSO Algorithm (MPSO)

To overcome the main deficiencies associated with a conventional PSO algorithm, a fuzzy self-adaptive mechanism is developed to adjust the inertia weight of a PSO algorithm when it's needed. For this purpose, two sets of triangular membership functions are proposed as shown in Fig. 2. The input set includes the normalized best fitness (NBF) and the inertia weight (ω) while the output set contains inertia weight correction factor ($\Delta\omega$).

$$\omega^{k+1} = \omega^k + \Delta\omega \quad (11)$$

To express the conditional statements which represent a

mapping from the input space to the output space the Mamdani fuzzy rule is adopted and the corresponding conditions are tabulated in Table I.

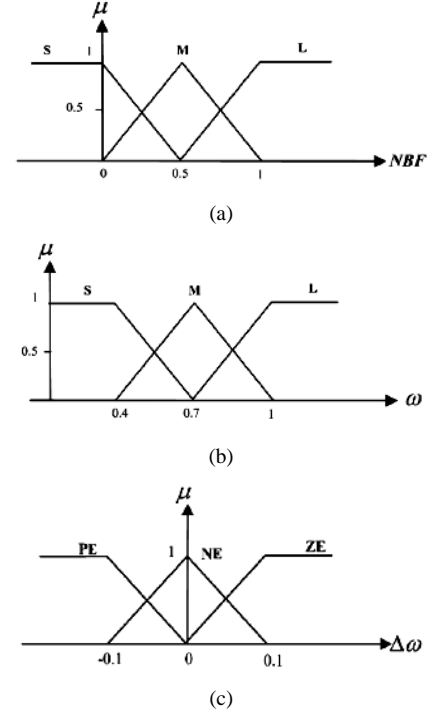


Fig. 2. Membership functions for weight correction factor fuzzification ((a),(b): Input variables – (c): Output variable)

TABLE I. FUZZY RULES FOR INERTIA WEIGHT CORRECTION FACTOR

$\Delta\omega$		ω		
		S	M	L
NBF	S	ZE	NE	NE
	M	PE	ZE	NE
	L	PE	ZE	NE

To implement the MPSO algorithm a hierarchical structure must be followed as below:

Step 1: Input data definition

The input data include: micro-grid configuration, operational characteristics of DGs and the utility, predicted output powers of WT and PV for a day ahead, hourly bids of DGs and the utility, emission coefficients of mentioned units, objective functions and the daily load curve.

Step 2: Program initialization

At the second step the program must be initialized by a set of random populations and their corresponding velocities as follows:

$$\begin{aligned} &\text{Population} = [X_1 \quad X_2 \quad \dots \quad X_{N_{\text{swarm}}}]^T \\ &X_0 = [x_0^1, x_0^2, \dots, x_0^n] \\ &x_0^j = \text{rand}(\cdot) \times (x_j^{\max} - x_j^{\min}) + x_j^{\min} \quad ; \quad X_i = [x_i^j]_{1 \times n} \\ &j = 1, 2, 3, \dots, n \quad ; \quad i = 1, 2, \dots, N_{\text{swarm}} \quad ; \quad n = 2 \times (N_g + N_s + 1) \end{aligned} \quad (28)$$

$$\begin{aligned} \text{Velocity} &= [V_1 \ V_2 \ \dots \ V_{N_{\text{swarm}}}]^T \\ V_i &= [v_i]_{1 \times n} \\ v_i &= \text{rand}(\cdot) \times (v_i^{\max} - v_i^{\min}) + v_i^{\min} ; \\ i &= 1, 2, 3, \dots, N_{\text{swarm}} ; \quad n = 2 \times (N_g + N_s + 1) \end{aligned} \quad (29)$$

where, n is the number of state variables, v_i and x_i are the velocity and position of the i^{th} state variable respectively. $\text{rand}(\cdot)$ is a random number between 0 and 1.

Step 3: do ($i=1$)

Step 4: Select the i^{th} individual and calculate the values of corresponding objective functions

Step 5: Store the i^{th} individual in the repository if it is a non-dominated solution

Step 6: Find the local best solution for the i^{th} individual ($P_{\text{best},i}$)

Step 7: $i=i+1$

Step 8: While ($i \leq N_{\text{swarm}}$) redo steps 4 to 7

Step 9: Select the global best (G_{best}) from the candidate solutions in the repository.

Step 10: Adjust the inertia weight using the fuzzy self-adaptive mechanism, update the population and find new solutions

Step 11: Check the termination criteria

If the maximum number of iterations executed by the MPSO is met or the desired error is reached, the optimization procedures is stopped, otherwise the population is replaced with the new generation and the algorithm is repeated from step 3.

VI. SIMULATION RESULTS

In this part of the work the proposed MPSO algorithm is implemented to solve the multi-operation management problem for the typical micro-grid shown in Fig. 1. To get a better insight to the solution domain in the corresponding search space, the problem is solved in three different cases including the main case, where all the units are dispatched regarding their real constraints, the second case in which both Renewable Energy Sources (RESs) (WT and PV) act at their maximum output powers (Max-Renw.) and the third case in which the utility can exchange energy with the micro-grid infinitely (Inf-Eng.Exch.). For the entire cases, a total energy demand of 1695kwh is considered for a typical day as shown in Fig. 3.

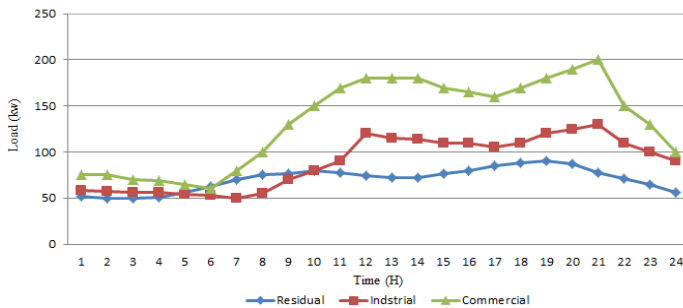


Fig. 3. Daily load curve in a typical Micro-Grid

The real-time market energy prices for the examined period are considered as Table II. Further information about DGs and their corresponding specifications are tabulated in Tables III-

IV. The maximum power outputs obtained from WT and PV are also estimated for a day ahead using an expert prediction model as shown in Fig. 4.

TABLE II. THE REAL-TIME MARKET PRICES [18]

Hour	Price (€/kWh)	Hour	Price (€/kWh)
1	0.23	13	1.50
2	0.19	14	4.00
3	0.14	15	2.00
4	0.12	16	1.95
5	0.12	17	0.60
6	0.20	18	0.41
7	0.23	19	0.35
8	0.38	20	0.43
9	1.50	21	1.17
10	4.00	22	0.54
11	4.00	23	0.30
12	4.00	24	0.26

TABLE III. INSTALLED DG SOURCES

ID	Type	Min Power (kW)	Max Power (kW)
1	MT	6	30
2	PAFC	3	30
3	PV	0	25
4	WT	0	15
5	Bat	-30	30
6	Utility	-30	30

TABLE IV. BIDS & EMISSIONS OF THE DG SOURCES

DG Type	MT	FC	PV	WT	Batt
Bid (€/kWh)	0.457	0.294	2.584	1.073	0.38
Start-up/Shut-down cost (€/t)	0.960	1.650	0	0	0
CO ₂ (kg/MWh)	720	460	0	0	10
SO ₂ (kg/MWh)	0.004	0.003	0	0	0.0002
NO _x (kg/MWh)	0.100	0.007	0	0	0.001

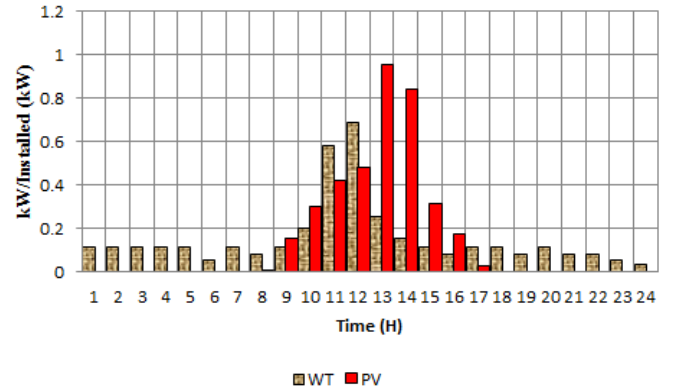


Fig. 4. Estimated power outputs from renewable energy sources [19]

Comparison of results in the case of each single objective for 20 trials of each optimization algorithm is shown in Tables V-VI respectively. It's observed from numerical results that the proposed MPSO algorithm demonstrates a better performance in the case of each objective minimization while maintains a low standard deviation in finding optimal solutions. Regarding the second scenario, it's investigated that the operating cost of the micro-grid increases greatly in comparison with the main case and demonstrates a growth of %72.2 in related cost. In

other words, although higher penetration of RESs into the grid environment results lower emission, it imposes higher cost of operation in short time period. In the last scenario, once again, it's observed that the proposed algorithm can solve the

optimization problem successfully while maintains small variations in finding optimal solutions considering both objectives.

TABLE V. COMPARISON OF PERFORMANCE RESULTS IN THE CASE OF COST OBJECTIVE FOR 20 TRIALS

	Main Case			Max. Renew			Inf-Eneg.Exch		
	NSGA II	PSO	MPSO	NSGA II	PSO	MPSO	NSGA II	PSO	MPSO
Best solution (€t)	162.395	163.466	160.797	278.578	275.611	275.255	91.558	90.990	90.197
Worst solution (€t)	200.300	181.850	161.118	305.503	288.619	275.556	128.082	108.132	90.268
Average (€t)	179.021	171.061	160.950	291.303	281.526	275.388	105.470	100.099	90.233
Std. deviation (€t)	11.481	6.134	0.097	10.385	4.045	0.092	13.434	5.884	0.030

TABLE VI. COMPARISON OF PERFORMANCE RESULTS IN THE CASE OF EMISSION OBJECTIVE FOR 20 TRIALS

	Main Case			Max. Renew			Inf-Eneg.Exch		
	NSGA II	PSO	MPSO	NSGA II	PSO	MPSO	NSGA II	PSO	MPSO
Best solution (€t)	439.153	438.736	438.733	436.121	436.121	436.121	437.061	435.919	435.904
Worst solution (€t)	459.567	448.816	438.925	450.120	439.536	436.274	459.747	449.862	436.087
Average (€t)	451.970	443.223	438.838	442.564	437.903	436.197	448.441	442.031	435.991
Std. deviation (€t)	6.498	3.740	0.069	5.285	1.270	0.059	7.033	4.881	0.061

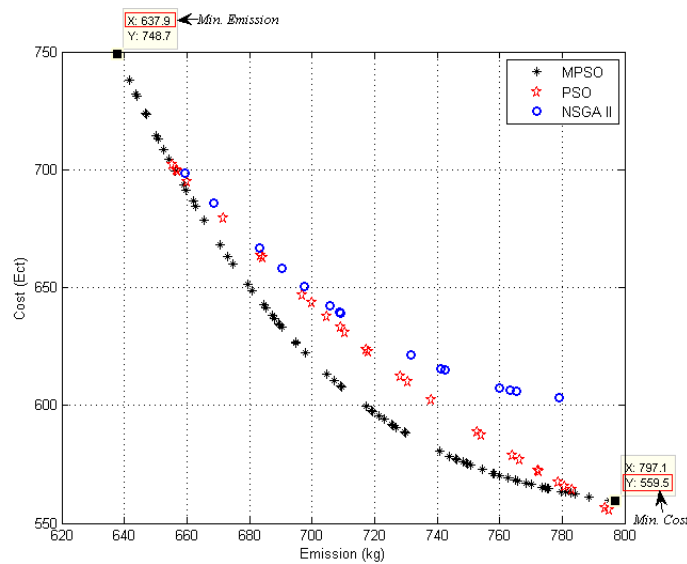


Fig. 5. Comparison of Pareto optimal fronts of all optimization algorithms

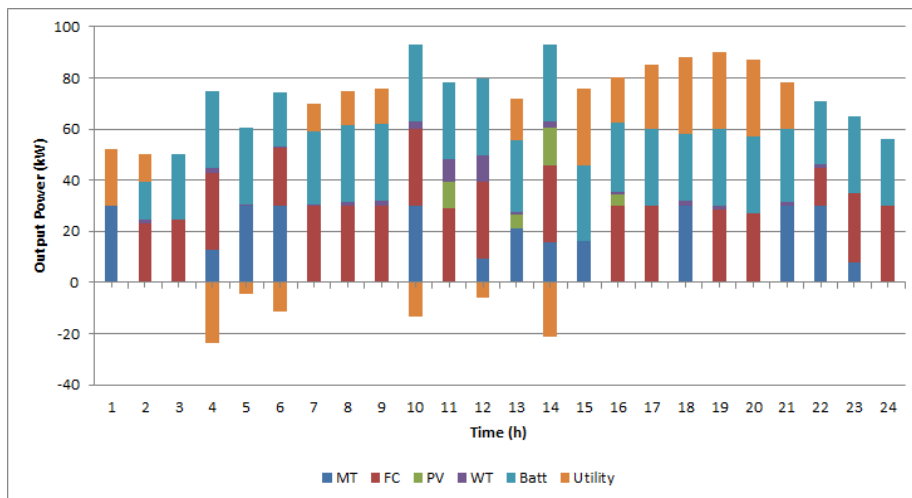


Fig. 6. Multi-operation management of units using MPSO (Total cost = 638 €t, Total emission = 748.9 kg)

Moreover, the numerical results indicate that allocation of optimal powers to DGs regarding an unlimited power exchange situation ends in a reduction of %43.5 in operation cost of the micro-grid in comparison with the main case. Now to incorporate the availability of DGs in optimization scheme while considering both objectives, suitable ON/OFF states (0/1) are assigned to DGs during the power dispatch process. In such situation, all the units are allowed to start up or shut down for the flexible operation of the micro-grid while considering minimum cost and emission as competitive objectives. In this regard, the Pareto fronts obtained by MPSO, PSO and NSGA II algorithms are shown in Fig. 5. It's observed from Fig. 5 that the non-dominated solutions achieved by the proposed MPSO algorithms are well-distributed over the Pareto front although the ones from standard PSO and NSGA II lack this feature and again the performances obtained by the proposed method outweigh the ones from other algorithms. The schedules of multi-operation management using MPSO regarding the left highlighted point indicated in Fig. 5 is shown in Fig. 6 as an illustrative example.

VII. CONCLUSION

In this paper, an adaptive modified PSO optimization algorithm is proposed and implemented to solve the combined Economic/Emission operation management problem in a typical micro-grid with renewable energy sources. To improve the performance of a standard PSO algorithm a Fuzzy Self Adaptive (FSA) mechanism is utilized for adjusting PSO parameters when they are needed. To evaluate the performance of the proposed algorithm several test cases are introduced and the simulation results are gathered subsequently. The numerical results indicate that the proposed method not only demonstrates superior performances but also shows dynamic stability and excellent convergence of the swarms. The proposed method also yields a true and well-distributed set of Pareto-optimal solutions giving the system operators various options to select an appropriate power dispatch plan according to environmental or economical considerations.

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