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Optimal energy management of a micro-grid with renewable energy resources and demand response

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With the introduction of smart energy grids and extensive penetration of renewable energy resources in distribution networks, Micro-Grids (MGs), which are comprised of various alternative energy resources and Advanced Metering Infrastructure (AMI) systems for better implementation of DR programs, are effectively employed. The design and development of Smart Energy Management Systems (SEMSs) for MGs are interesting and attractive research problems. In this paper a new SEMS architecture is presented to solve the multi-objective operation management and scheduling problem in a typical MG while considering different energy resource technologies, Plug-in Hybrid Electric Vehicles (PHEVs) and DR programs. The energy management problem is formulated as a constrained mixed integer nonlinear multi-objective optimization problem, in which the MG's total operating cost and net emissions must be minimized simultaneously. Three different optimization algorithms are used to solve the above mentioned problem and their outputs (Pareto optimal solutions) for the same problem are compared and analyzed. © *2013 AIP Publishing LLC*. [http://dx.doi.org/10.1063/1.4826880]

I. INTRODUCTION

In recent years, growing trend of energy consumption and environmental pollutions has made energy crisis a highly challenging problem in modern societies.[1,2] Moreover, some technical issues in power systems such as reliability, power quality, and power losses have led to noticeable concerns for utilities. In this regard, using Distributed Generation (DG) units in power systems has been considered as a valuable solution.[3] Generally, DG is defined as a small scale energy producer that feeds local loads.[4,5] Distributed generators have various types such as Wind Turbine (WT), Photo-Voltaic (PV) panel, Fuel Cell (FC), Micro-Turbine (MT), Diesel generator (D), and battery.[2,11,12] Some advantages of using Distributed Energy Resources (DERs) can be declared as mitigation of energy crisis, environmental sustainability, reducing distribution and transmission costs and, improving power quality and reliability.[2] Recent research works show that by increasing the penetration of DERs up to 20%, the CO_2 emissions could be reduced by 2.07%–4.85%.[1]

The Plug-in Hybrid Electric Vehicles (PHEVs) have become popular due to their impacts on reducing emission, inexpensive charging and diminishing fossil fuels usages. The PHEVs have two operation modes, known as Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) modes. Recent research works at NREL institute show that using these vehicles can significantly reduce emissions, produced by the vehicles in transportation systems.[7,8]

The MG in its whole vision is a collection of various loads and DGs, which can operate in grid connected and islanded modes.[9,10] Due to the ability of MGs to operate in islanding mode and feed their loads with their built-in energy resources they can increase the power quality and reliability.[9,10] The utilization of small-modular residential, commercial, and industrial units for onsite service is the most important applications of the integrated units.[14,18] The optimal performance management and control of DGs together with effective participation of consumers in DR programs is one of the most important tasks of MGs which is handled by an energy management module.[15,17]

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According to recent research, using energy management methods in residential sector can reduce power consumption from 20% to 30%.[16,18] A Smart Energy Management System (SEMS) has been presented by Chen *et al*.[17] for optimal operation of a MG where distribution generation units satisfy existing loads considering cost minimization. In the mentioned case study, hourly wind speed and radiation data have been estimated via an expert forecasting module. In a similar manner, Bagherian *et al*. have designed a SEMS for optimal operation of a MG with different types of technologies and load models considering maximum profit as objective function.[19] In this case, interruptible load has been considered as a part of DR program. Such a similar model has been proposed in Ref. 18 where reduction of energy production costs in buildings has been considered as an objective considering several constraints and uncertainties. Likewise, optimal operation management of a MG considering Demand Side Management (DSM) is presented in Ref. 13, where load models are considered as residential, industrial, and commercial. System modeling and online optimal management of MGs using multi-objective optimization techniques has been also described in related literatures where the purpose of a SEMS module has been considered to be emission reduction, loss minimization, energy consumption reduction, cost minimization, or profit maximization.[20]

In this paper, the proposed SEMS is formulated as a mixed integer nonlinear problem implemented in GAMS environment and is solved by CPLEX solver.[21] Although lots of researches have been done in the field of energy management recently, rarely can be found a precise model to handle the problem, hence there is a strong need to develop an expert SEMS architecture to simplify the scheduling problem and complete the previous models.

The proposed SEMS architecture considers different objective functions, various technologies, and new concepts such as DR programs. Three different optimization methods have been used to solve the multi-objective function and the results have been gathered subsequently. The reset of the paper is organized as follows: Sec. II provides a model for the SEMS. The multi-objective operation management problem is presented in Sec. III. Section IV describes the fundamentals of multi-objective optimization together with different approaches used for solving the mentioned problem. Components of the sample MG as well as a brief description of the case study are discussed in Sec. V. Finally, Sec. VI deals with the implementation of the proposed algorithm to the optimization problem and demonstration of simulation results.

II. SEMS MODEL

The generic model of the proposed SEMS is shown in Figure 1. As can be seen in this figure, this model includes three hierarchical layers named as physical, pre-processing, and processing. These layers are briefly described in the following sections:

- **Physical layer:** As mentioned before, a MG consists of different loads and generation technologies. In the physical layer generating units and consumers are introduced separately. In generation part, units are classified into renewable resources, energy storage options, dispatchable DGs, and the utility or the macro-grid. In demand side, loads are classified into two parts: schedulable and non-schedulable loads. Schedulable loads such as washing machines and air conditioners are the ones that have the ability to participate in DR programs. Therefore, the DR control signals will be applied to them. Non-schedulable loads such as lighting are the ones which cannot be shifted or curtailed upon the request from a system operator.
- **Preprocessing layer:** This layer consists of two important parts which are called forecasting and management modules. The forecasting module applies the required data for the processing layer such as irradiation, load and price data. Moreover Energy Storage Systems (ESSs) such as batteries and FCs can be used effectively for saving energy during off-peak periods, yet there are some constraints such as State of Charge (SOC) and Depth of Discharge (DOD), which must be met properly. In an management module the storage options are planned and managed suitably considering the limits mentioned beforehand. However, other factors such as battery lifetime, number of charge and discharge cycles and temperature limit can be managed in this module.
- **Processing layer:** Having received the required information from the previous layers, the processing layer provides optimal set points for the generating units and schedulable loads using

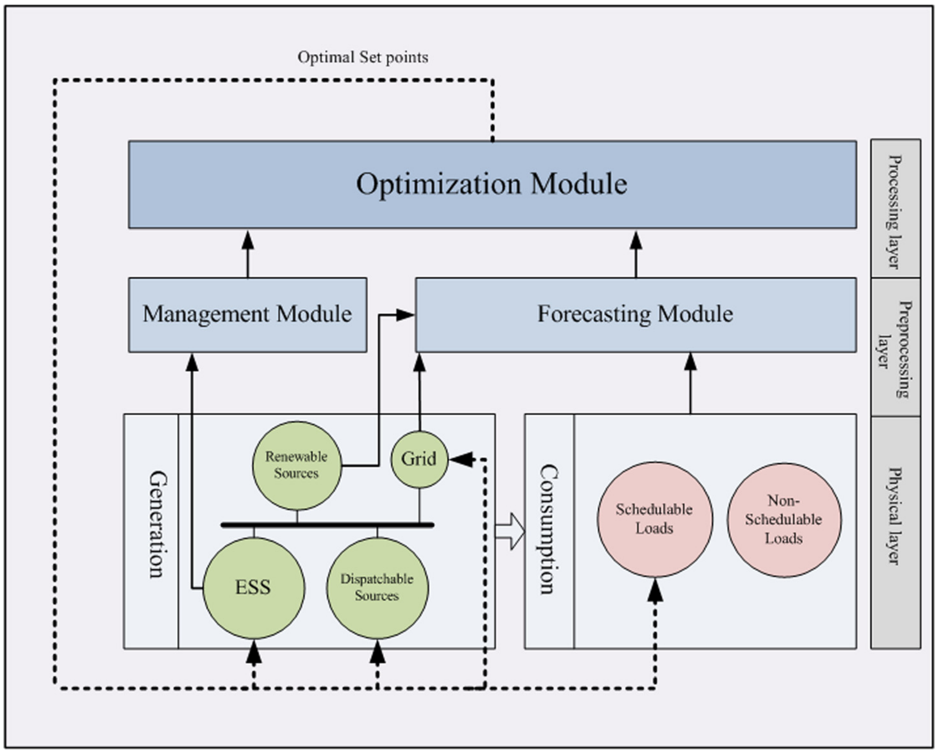

FIG. 1. SEMS architecture.

appropriate optimization algorithms. In other words, the modules corresponding to the last layer, analyze the received information, and make a plan in a way to optimize the objective functions considering the existing constraints.

III. PROBLEM FORMULATIONS

As stated earlier, the role of an energy management system in a MG is to supply the load from various energy resources in an optimized manner. The required amount of energy can be supplied from distributed generators such as MTs, PV panels, WTs, Ds, FCs, and batteries or provided from the utility. In a MG, some environmental parameters affect the output power of renewable-based generators such as PVs and WTs. In this case, their output power must be forecasted based on meteorological information. According to the forecasted data, the purpose of the SEMS is to optimize the objective functions while satisfying limits and network constraints. In this paper, objective functions of SEMS are the cost and emission minimization over a 24-h period. The cost function includes operation cost, start-up/shut-down cost, energy storage cost, cost of DR programs, and power exchange cost,

$$\begin{aligned}\mathrm{Min\,TC(P)} &= \sum_{t=1}^{T}\{C_{DG}(t)+ST_{DG}(t)+C_{ESS}(t)+C_{Grid}(t)+C_{DR}(t)\}\\ &= \sum_{t=1}^{T}\left\{\begin{array}{l}\displaystyle\sum_{i=1}^{L}[u_i(t)P_{Gi}(t)B_{Gi}(t)+S_{Gi}|u_i(t)-u_i(t-1)|]\\ \displaystyle+\sum_{j=1}^{M}[u_j(t)P_{essj}(t)B_{essj}(t)]\\ +u_{Buy}(t)P_{Grid}(t)B_{Grid\_Buy}(t)\\ -u_{Sell}(t)P_{Grid}(t)B_{Grid\_Sell}(t)+P_{DR}(t)B_{DR}(t)\end{array}\right\},\end{aligned} \tag{1}$$

where T is the total number of hours, L and M are the total number of generators and storage units, $u_i(t)$ and $u_j(t)$ are status of i^{th} DG and j^{th} storage, $u_{Buy}(t)$ and $u_{Sell}(t)$ are status of power bought (sold) from (to) the utility, $P_{Gi}(t)$, $P_{essj}(t)$ and $P_{Grid}(t)$ are the power production of i^{th} DG, j^{th} storage, and the grid, respectively, $P_{DR}(t)$ is the amount of power contributed in a DR program, S_{Gi} is the start-up or shutdown cost, $B_{Gi}(t)$ and $B_{essj}(t)$ are the bids of i^{th} DG and j^{th} storage, $B_{Grid\_Buy}(t)$ and $B_{Grid\_Sell}(t)$ are the bids from the utility when buys(sells) energy from(to) the MG, $B_{DR}(t)$ is the cost of contribution in a DR program and $P_{Demand}(t)$ is the amount of load at hour t.

Likewise, the emission function includes the amount of emission from DGs, storages, and the grid and can be formulated as follows:

$$\begin{aligned}\mathrm{Min\,TE(P)} &= \sum_{t=1}^{T}\{E_{DG}(t)+E_{ESS}(t)+E_{Grid\_Buy}(t)\}\\ &= \sum_{t=1}^{T}\left\{\begin{array}{l}\sum_{i=1}^{L}[u_i(t)P_{Gi}(t)E_{Gi}(t)]+\sum_{j=1}^{M}[u_j(t)P_{essj}(t)E_{essj}(t)]\\ +u_{Buy}(t)P_{Grid}(t)E_{Grid}(t)\end{array}\right\},\end{aligned} \tag{2}$$

where $E_{Gi}(t)$ and $E_{essj}(t)$ are the amount of gas emitted from i^{th} DG and j^{th} storage and $E_{Grid\_Buy}(t)$ is the amount of emission from the grid at hour t. Both objective functions should be minimized simultaneously, considering the following constraints:

- Power supply balance:

$$\begin{aligned}&\sum_{i=1}^{L}P_{Gi}(t)+\sum_{j=1}^{M}P_{essj}(t)+u_{Buy}(t)P_{Grid}(t)-u_{Sell}(t)P_{Grid}(t)\\ &=P_{Demand}(t)-u_{Curtail}(t)P_{Curtail}(t)-u_{diff\_\mathrm{Req}}(t)P_{diff}(t)+u_{diff\_non\mathrm{Req}}(t)P_{diff}(t),\end{aligned} \tag{3}$$

where $P_{curtail}(t)$ and $P_{diff}(t)$ are the amount of curtailed and deferred loads, respectively, and $u_{diff\_Req}(t)/u_{diff\_nonreq}(t)$ are the status of deferrable loads in a DR program at hour t.

- Status of power exchange between MG and the utility:

$$u_{Buy}(t)+u_{Sell}(t)\le 1. \tag{4}$$

- Power generation limit:

$$\begin{aligned}P_{Gi,\min}&\le P_{Gi}(t)\le P_{Gi,\max}\\ P_{essj,\min}&\le P_{essj}(t)\le P_{essj,\max}\\ P_{grid,\min}&\le P_{Grid}(t)\le P_{grid,\max}.\end{aligned} \tag{5}$$

- Battery charge/discharge constraints:

$$\begin{aligned}&Q_j(t)=Q_j(t-1)-\frac{1}{\eta_{Dj}}u_{Dj}(t)P_{essj}(t)+\eta_{Cj}u_{Cj}(t)P_{essj}(t)\\ &u_{Dj}(t)+u_{Cj}(t)\le 1;\; Q_{\min}\le Q_j(t)\le Q_{\max};\quad Q_j(1)=Q_e,\end{aligned} \tag{6}$$

where $Q_j(t)$ is the SOC, $u_{Cj}(t)/u_{Dj}(t)$ are the status of charging/discharging for the j^{th} storage device, η_{Dj} and η_{Cj} are discharging/charging efficiencies of j^{th} storage and Q_e is initial SOC at hour t. The first equation illustrates charge/discharge process while the second one shows that charge and discharge processes cannot occur simultaneously at any time. Initial SOC has been indicated in the last equation.

- Spinning reserve constraint:

$$\sum_{i=1}^{L}\{P_{\max,i}-P_i(t)\}+\sum_{j=1}^{M}\{P_{\max,j}-P_{essj}(t)\}+(P_{\max,grid}-P_{grid}(t))-P_{Demand,total}(t)\geq RESV(t). \tag{7}$$

According to Eq. (7), the spinning reserve capacity (RESV) is defined as the total amount of maximum unit set-point of all committed units minus total demand at each hour. Spinning reserve must be sufficient enough to maintain the desired reliability of a power system. It is usually a pre-specified limit or equal to the largest unit or a given percentage of the forecasted demand, usually is equal to 10%.

- DR constraint

$$\begin{aligned}&P_{curtail,\min}(t)\leq P_{curtail}(t)\leq P_{curtail,\max}(t)\\&P_{diff,\min}(t)\leq P_{diff}(t)\leq P_{diff,\max}(t)\\&\sum_{t=1}^{T}\{u_{diff\_\mathrm{Req}}(t)P_{diff}(t)-u_{diff\_non\mathrm{Req}}(t)P_{diff}(t)\}=0.\end{aligned} \tag{8}$$

According to Eq. (8), the loads inside a typical MG can be classified into three major categories: critical, curtailable, and deferrable loads. The critical loads have high priorities and cannot be shed. Curtailable loads can be shed, if an emergency condition occurs. Likewise, deferrable loads (e.g., washing machine) can be shifted from peak time to off-peak periods upon the MGCC request.

IV. MULTI-OBJECTIVE OPTIMIZATION

Many real-world optimization problems are dealing with finding optimal solutions considering different objectives simultaneously. In a multi-criteria optimization problem, since a particular solution isn't the best with regard to all objectives, a set of optimal solutions known as Pareto-optimal are introduced instead. Generally, in a multi-objective optimization problem different objective functions are required to be optimized simultaneously considering a set of equality and inequality constraints as follows:

$$\begin{aligned}&\text{Minimize}\quad F=[f_1(X),f_2(X),\ldots,f_n(X)]^T\\&\text{Subject to}:\begin{cases}g_i(X)<0 & i=1,2,\ldots,N_{ueq}\\ h_i(X)=0 & i=1,2,\ldots,N_{eq},\end{cases}\end{aligned} \tag{9}$$

where F is a vector including objective functions and X is a vector containing 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. For a multi-objective optimization problem, any two solutions X and Y can have one of these two possibilities: one dominates the other or none dominates the other. In a minimization problem, without loss of generality, a solution X dominates Y if the following two conditions are satisfied:

$$\begin{aligned}&\forall j\in\{1,2,\ldots,n\},\ f_j(X)\leq f_j(Y)\\&\exists k\in\{1,2,\ldots,n\},f_k(X)<f_k(Y).\end{aligned} \tag{10}$$

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 solution to be stored in the repository of non-dominated solutions.

A. Fuzzy weighted sum method (FWSM)

In a FWSM, a fuzzy-based clustering approach is applied to store the non-dominated solutions in a predefined and finite-size repository. In this regard, first a fuzzy membership function is used to evaluate each objective function related to any individual inside the repository as follows:[22,23]

$$\mu_{fi}(X) = \begin{cases} 1, & f_i(X) \leq f_i^{\min} \\ 0, & f_i(X) \geq f_i^{\max} \\ \dfrac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}}, & f_i^{\min} \leq f_i(X) \leq f_i^{\max}, \end{cases} \tag{11}$$

where f_i^{min} and f_i^{max} are the lower and upper bounds of i^{th} objective function, respectively. In the proposed algorithm, the values of f_i^{min} and f_i^{max} are evaluated by optimizing each objective function separately. In the next step, the normalized membership value is calculated for each element inside the repository, as follows:

$$N\mu(j) = \frac{\sum_{k=1}^{n} \omega_k \times \mu_{fk}(X_j)}{\sum_{j=1}^{m} \sum_{k=1}^{n} \omega_k \times \mu_{fk}(X_j)}, \tag{12}$$

where m is the number of non-dominated solutions, ω_k is the weight factor for k^{th} objective function. The normalized membership value is a decisive criterion used for storing the best non-dominated solutions in the repository.

B. ε-Constraint method

This method is based on converting a multi-objective optimization problem into a Single objective one. A mathematical formulation of a multi-objective function is presented in Eq. (13). It minimizes the whole objectives considering equality and inequality constraints. In a

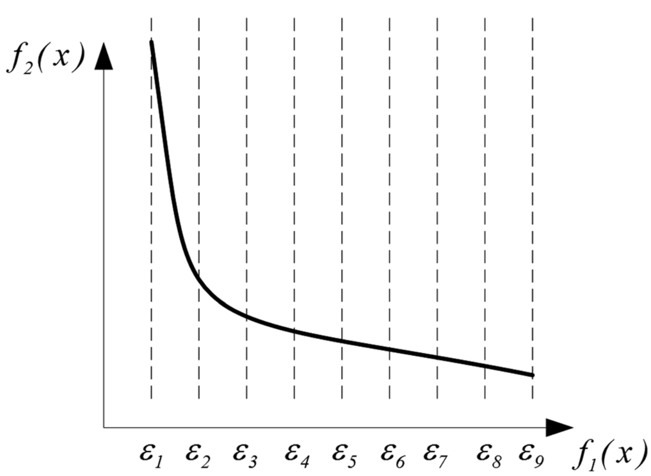

FIG. 2. Geometric description of two-dimensional ε-constraint.[24]

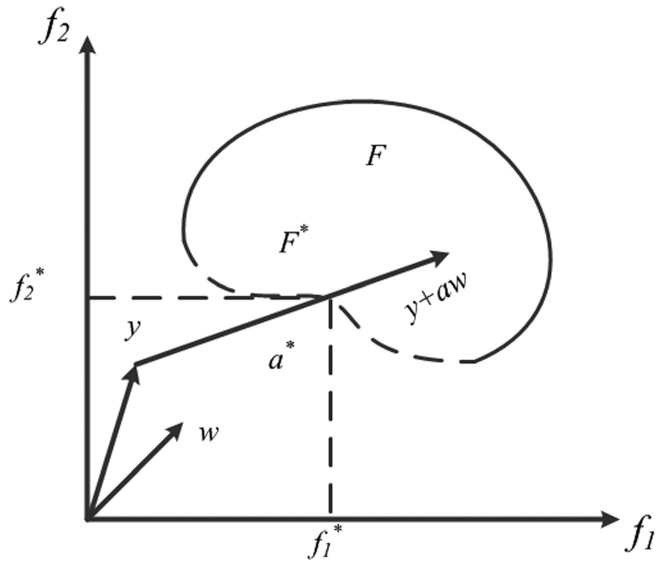

FIG. 3. Geometric description of two-dimensional GAM.[21]

ε-constraint method, Eq. (13) can be rewritten as Eq. (14) in which one of the objectives is considered as the main objective and the other objectives are treated as constraints. By variation of the constraint bounds, different Pareto fronts can be achieved,[24]

$$\begin{aligned} &Min.\ \mathrm{F(x)} = \{f_i(x), \ldots, f_n(x)\} \\ &\text{s.t. } g(x) \le 0, h(x) = 0, \end{aligned} \tag{13}$$

$$\begin{aligned} &Min. F(x) = f_i(x) \\ &\text{s.t } f_i(x) \le \varepsilon_j,\ j = 1, 2, \ldots, n\ \ \&\ \ j \ne i \\ &g(x) \le 0,\ h(x) = 0, \end{aligned} \tag{14}$$

where $g(x)$ is the vector of inequality constraints, $h(x)$ is the vector of equality constraints, i and j are the main and the constraint objective function indices, respectively. In this method with a very small change in value of epsilon (ε) for each constraint, a set of solutions are obtained. The epsilon (ε) value should be wisely chosen in a way not to miss any Pareto optimal solution because of the fact that choosing very small values can cause a large number of redundant solutions. This method has been shown in Figure 2.

C. Goal attainment method (GAM)

The main idea of this method is to find solutions in a way to meet a predetermined target. Through the solution space, if there is no solution to satisfy the optimal operation, the optimization algorithm tries to find a solution with the lowest deviation from the optimal point. This method is a powerful tool to find the best-compromised solution in multi-objective problems,

$$\begin{aligned} &Min \cdot \sum p_i \\ &\text{s.t } f_i - \alpha_i p_i \le f_i^*,\ i = 1, 2, \ldots, n, \end{aligned} \tag{15}$$

where $f_i(x_i)$ is the i^{th} objective function, α_i is the weighting vector, p_i is the slackness scalar variable vector, f_i^* is the designed goals vector, and x_i is the vector of control variables. Equation (15) shows that in a multi-objective problem with variation of weighting vectors, relative tradeoffs between objectives are achieved. Objectives will reach to their optimum values by minimizing slack variables. Therefore, in a multi-objective problem, each slack variable tries to optimize its own objective function. Tradeoff between these variables will result in best solution. This method has been shown in Figure 3.

Slack vector determines the direction of $f_i^* + \alpha_i p_i$ in the solution space and the weighting vector determines the closest intersection of $f_i^* + \alpha_i p_i$ with the horizontal axis, with respect to the origin considering the best solution in the search space.[25]

V. CASE STUDY

In this section, a typical Low Voltage (LV) MG is considered as a test case as shown in Figure 4. This network consists of three different feeders: residential, commercial, and industrial consumers. The daily load curve for the mentioned feeders in a typical day is shown in Figure 5 which represents the energy demand of 1705 kWh for the examined period.[6] The MG also includes various DG resources such as MT, D, PV, and WT as well as storage options such as FC and battery.

Table I shows the operating limits of DGs and their available units in the model. The power factor for all DGs is assumed to be unity. In this L.V network, there exist 10 battery units with the capacity of 16 kWh and the maximum charging power of 4 kW according to residential feeder maximum current and voltage that are assumed to be 16 A and 230 V, respectively. The SOC of batteries is considered between 20% and 100% of their rated capacities. Finally, charging/discharging efficiency is assumed to be 0.94.

Similarly, Table II illustrates bid coefficients, start-up and shut-down cost of DG sources.

To simplify our analysis, start-up/shut-down costs are assumed to be equal. Furthermore, it's assumed that all DGs operate in electrical mode and no heat is produced or absorbed during the operation period. The normalized estimated power obtained from WT and PV is shown in Figure 6. Table III presents the amount of gas emitted from DGs and the grid in kg/MWh, as well. Market energy prices, has been also taken from Amsterdam Power Exchange (ApX) for a given day and is shown in Figure 7.[6] It's noteworthy to say that the DR program has considered two load types: curtailable and deferrable loads. These loads are categorized into high and low priority ones with different price tariffs. It is also assumed that all kinds of loads can be shifted

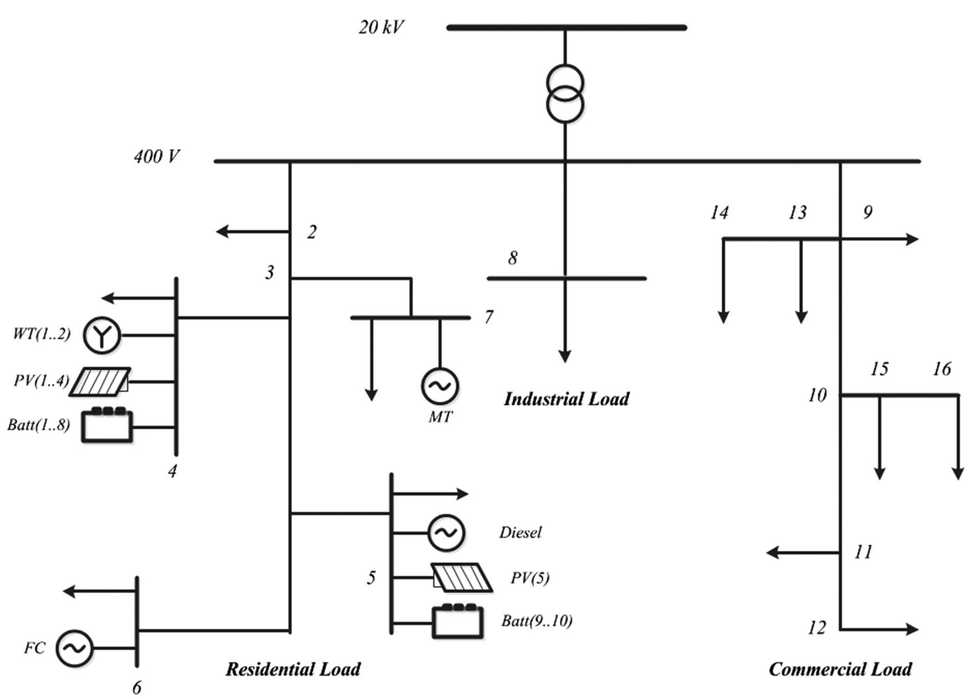

FIG. 4. A typical L.V micro-grid.[6]

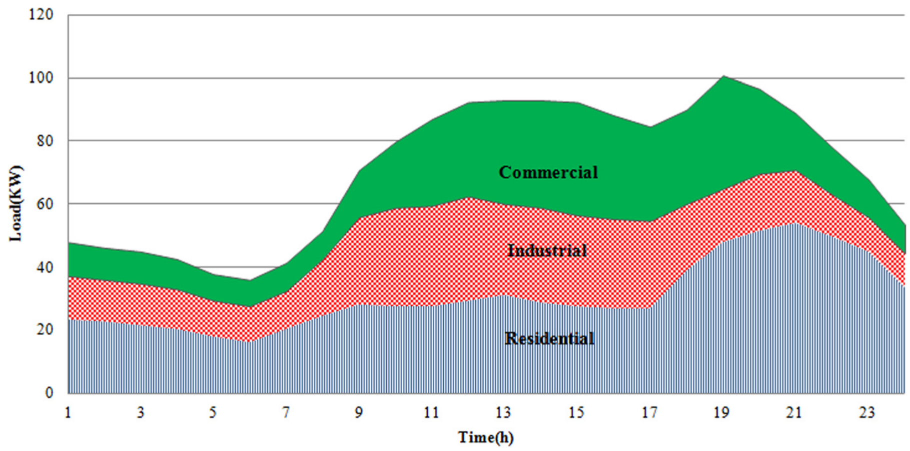

FIG. 5. Typical daily load profiles for the mentioned MG.[6]

TABLE I. Technical specifications of energy sources.[6]

Type	Min. power (kW)	Max. power (kW)	Number
MT	6	30	1
FC	3	30	1
D	0	30	1
PV	0	25	5
WT	0	15	2
Bat	−4	4	10
Grid	−70	70	1

TABLE II. Bid coefficients of DGs.[6]

Type	a_i (Ect/kWh)	b_i (Ect/h)	Start-up/shut-down cost (Ect)
MT	4.37	85.06	9
FC	2.84	255.18	16
D	3	20	0
PV	54.84	0	0
WT	10.63	0	0
Bat	4.43	0	0

but only residential load can be curtailed. The maximum amounts of loads that can be curtailed and deferred upon the operator request are assumed to be 5% and 2% of the total demand in each feeder, respectively. Besides, the deferral price tariffs for high and low priority loads are 6.9 and 69 Euro Cent (Ect) per kWh, respectively, while the prices for the curtailable loads are considered as 13.8 and 138 Ect per kWh, respectively.[18]

PHEVs availabilities based on historical data for a 24-h period is shown in Figure 8. PHEVs usually travel in a period of time from 7 to 21; hence their availabilities are reduced in these hours.[26]

VI. NUMERICAL RESULTS

In this part of the work, the proposed optimization algorithms are implemented to solve the operation management problem and their performances are compared. In the suggested model,

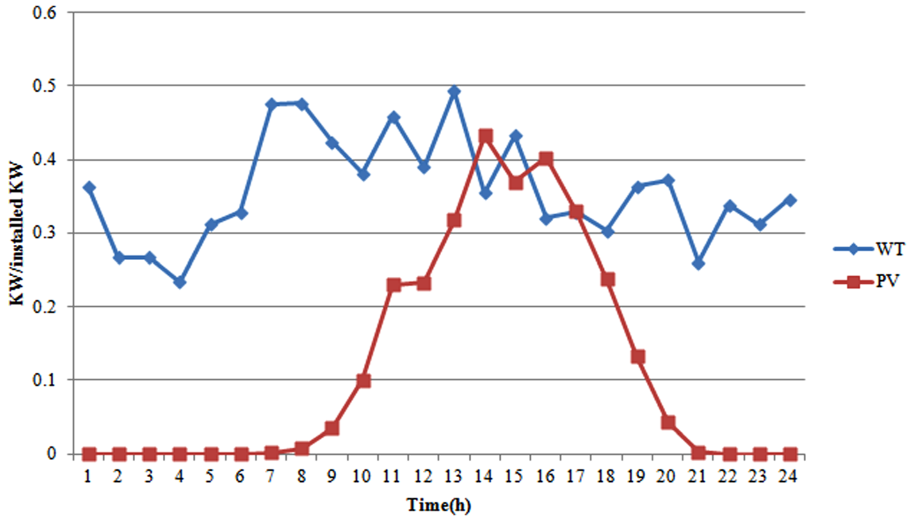

FIG. 6. Normalized estimated power outputs from WT and PV.[6]

TABLE III. Gas emission of DG sources and grid.[23]

Type	CO_2 (kg/MWh)	SO_2 (kg/MWh)	NO_x (kg/MWh)
MT	720	0.0036	0.1
FC	460	0.003	0.0075
D	650	0.23	10
PV	0	0	0
WT	0	0	0
Batt	10	0.0002	0.001
Grid	950	0.5	2.1

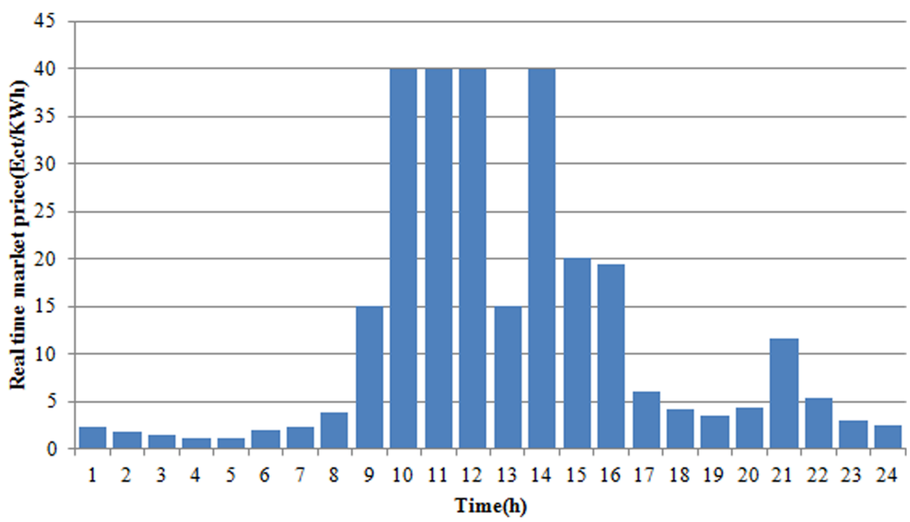

FIG. 7. Real-time market prices from ApX on October 8, 2003.[6]

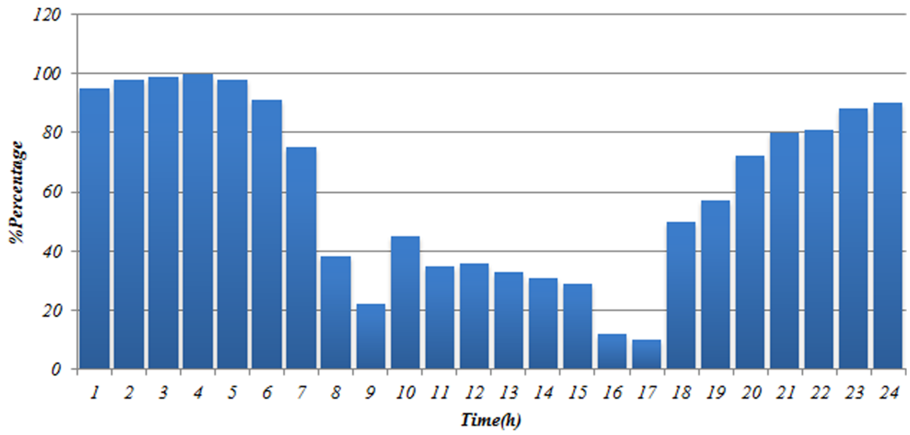

FIG. 8. PHEVs availability.[26]

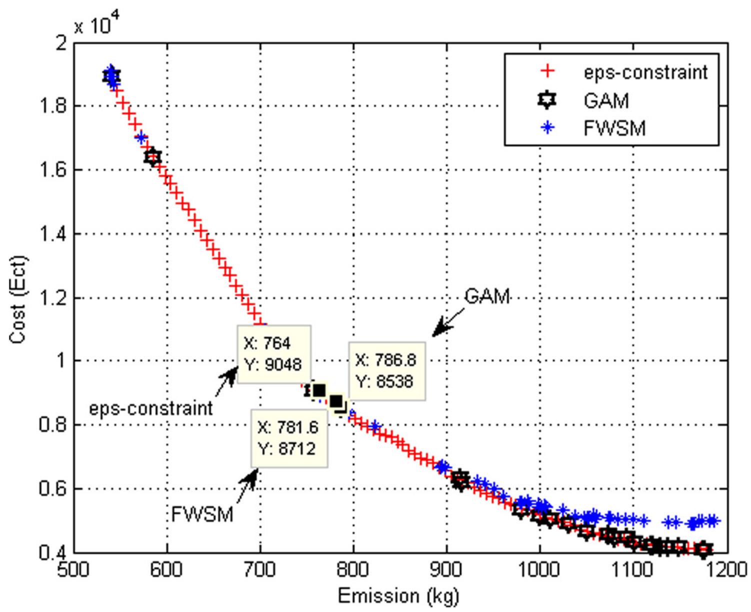

FIG. 9. Comparison of emission and cost Pareto optimal fronts.

the objective function considers both the total cost of the micro-grid which includes power generation costs and start-up/shut-down costs of units and the net emission of pollutants. For the proposed MG shown in Figure 3, the optimization problem is formulated deterministically. Based on forecasted values of wind speed and solar radiation, multi-objective scheduling problem is solved by a CPLEX Solver using GAMS software. The Pareto front for emission and cost objectives obtained by mentioned algorithms is shown in Figure 9.

The best compromised solutions and the simulation times have been shown in Table IV. The Normalized Best Fitness (NBF), which is a decisive value for determining the best solutions, for each multi-objective method is calculated according to Eq. (11) and is indicated in this table. It is also noteworthy to say that the weight factor for emission objective is considered more than the one for the cost objective. As observed from the mentioned table, the best NBF belongs to the ε-constraint method considering both objectives, so it is chosen as the desired method in this paper. Likewise, the schedule of multi-operation management inside the MG is shown in Figure 10 through ε-constraint method. The numerical results indicate that for

TABLE IV. Comparison of solutions in three methods.

Methods	Simulation time (s)	Cost (Ect)	Emission (kg)	NBF
ε-Constraint	18.063	9048	764.0	0.893
FWSM	242.23	8712	781.6	0.832
GAM	12.803	8538	786.8	0.886

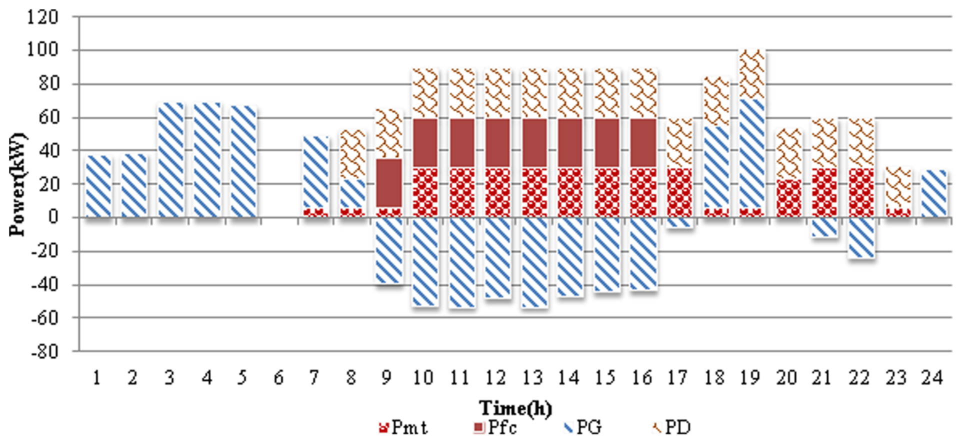

FIG. 10. Optimal dispatch of units and grid.

a certain period of time (from 9:00 to 17:00) when the energy prices are high, the surplus of power is sold to the utility and in this way, the MG revenue increases. Conversely, the utility takes the lead in supplying the load inside the MG during the first hours of the day when there exists low price spikes.

The amount of energy bought from and sold to the grid is 421 kWh and 488 kWh, respectively. The cost of energy bought from and sold to the grid is 1091.6 Ect and 11418.4 Ect, respectively, where this huge difference comes from the difference between cost of energy in peak and non-peak hours. Generally the profit resulting from exchanging power with the grid is 10326.8 Ect that can cover production cost of other devices too.

The participation of loads in DR programs is also shown in Figure 11. As observed from the figure, both curtailable and deferrable loads can be curtailed and deferred between 9:00 and 16:00, respectively, when the electricity tariffs are high. It should be noted that the deferred loads can be fed in other times with cheaper tariffs in a way that the total consumed and curtailed demand equals to zero. The amount of curtailable loads is 34.9 kWh and a cost of 481.6 Ect due to consumers' participation in this program is paid to them. Also the total amount of these loads in peak hours is 14 kWh and a cost of 96.3 Ect will be paid by utility to consumers in this regard.

The hourly cost and the cumulative cost of power exchange with grid are shown in Figure 12. As seen in this figure, the hourly cost due to power exchange with grid has been increased when the market price is high. And also the cumulative cost of power exchange is decreased because of the power sold to the grid.

Moreover, the control signals for charge/discharge process ("1" for charging and "−1" for discharging) or idle condition ("0") of hybrid electric vehicles are shown in Figure 13. Charge and discharge process of hybrid electric vehicles is also shown in Figure 14. It's observed from the simulation results that the charging processes of the batteries are done at the first hours of the day when the prices are low but the discharge actions are postponed to the midday when the load curve reaches peak values.

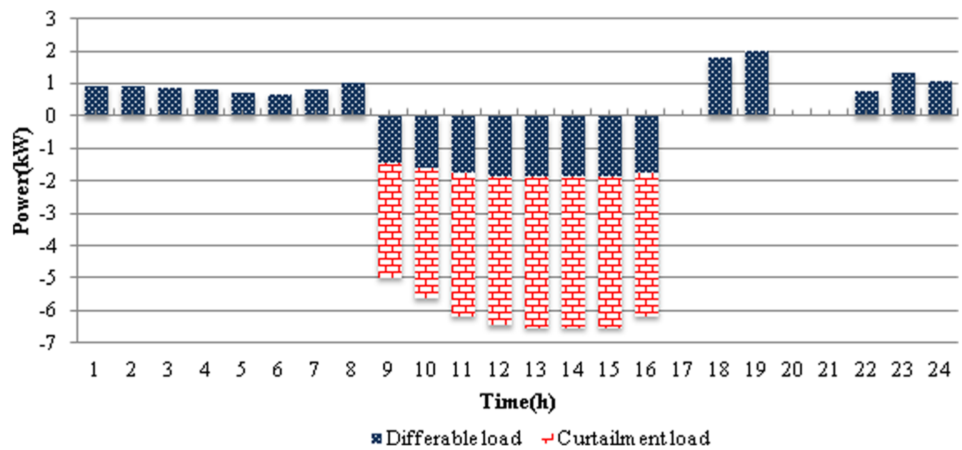

FIG. 11. Participation of loads in DR program.

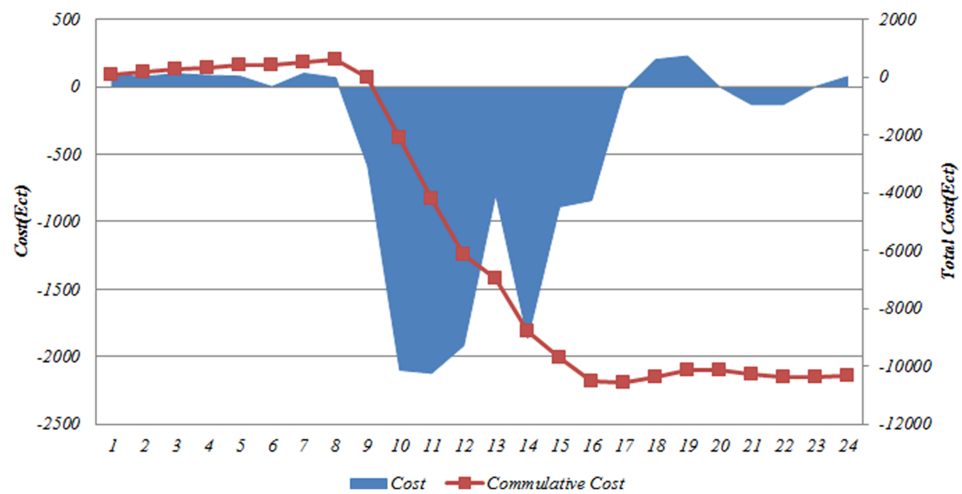

FIG. 12. Hourly cost and cumulative cost of power exchange with grid.

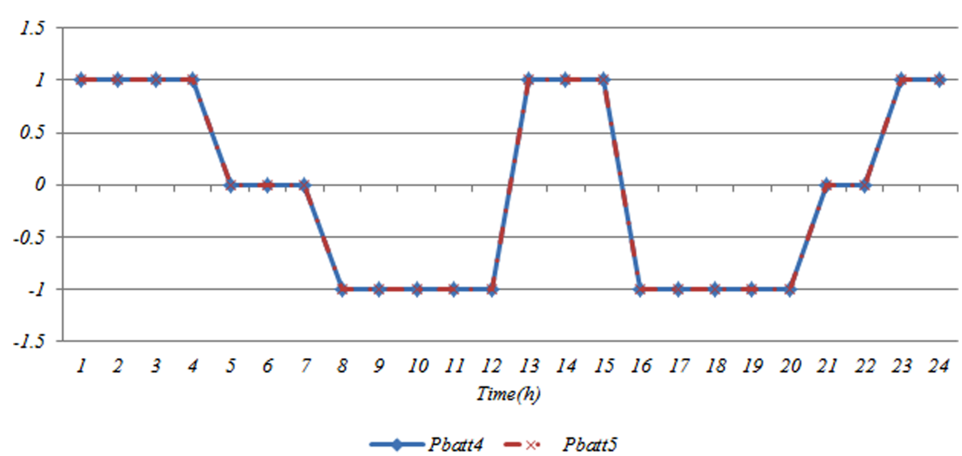

FIG. 13. Control signal of PHEVs batteries.

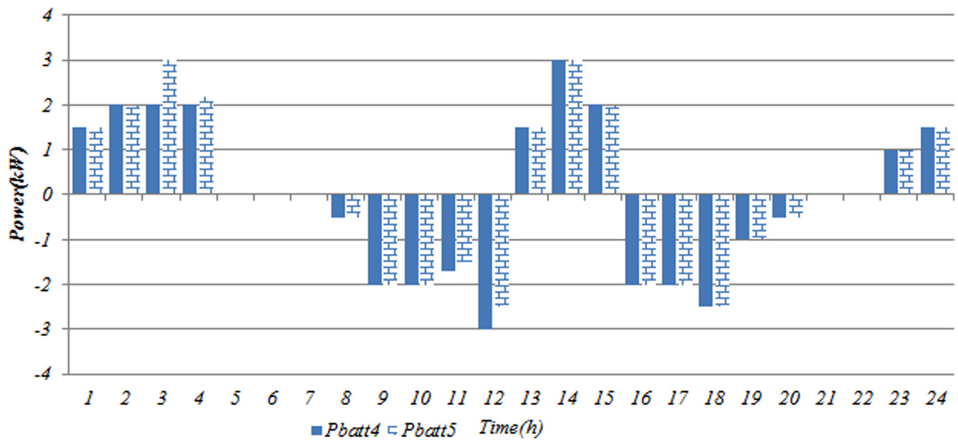

FIG. 14. Charging and discharging power production of PHEVs batteries.

VII. CONCLUSION

In this paper, three different multi-objective optimization algorithms are proposed and implemented to solve the multi-objective energy management problem in a typical MG with high penetration of renewable energy resources considering the effects of PHEVs and DR programs. To evaluate the performance of the proposed algorithm, a test system is introduced and the simulation results are gathered subsequently. The numerical results indicate that the ε-constraint method not only demonstrates superior performances in the case of both objective functions minimization but also yields a true and well-distributed set of Pareto-optimal solutions giving the system operators various options to select an appropriate power dispatch scheme.

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