Impact Assessment of Profit and Emission Objectives on the Operational Scheduling of a Virtual Power Plant

H. A. Shayanfar[1], **H. Karimipour**[2], **and S. Hadayeghparast**[2]
[1] College of Technical & Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran
[2] Department of Engineering, University of Guelph, Guelph, Canada
hashayanfar@gmail.com, hkarimi@uoguelph.ca, shadayeg@uoguelph.ca

Abstract – *Global warming is among the most important global issues. Therefore, environmental issues should be considered in power systems for contributing to emission reduction. This paper presents multi-objective economic/emission operational scheduling of a Virtual Power Plant (VPP) participating in day-ahead market. The optimization problem is modeled by two-stage stochastic programming considering uncertainties. Multi-objective Particle Swarm Optimization (PSO) is used for solving the nonlinear and non-convex problem and generating Pareto-optimal solutions. Impact assessment of profit and emission objectives on the operational scheduling of VPP is conducted by analyzing specifications of each Pareto-optimal solution. The results indicate the significant influence of profit and emission objectives on the scheduling of Distributed Energy Resources (DERs) and power exchanged with the electricity market. Also, about 60% reduction in profit and around 50% decrease in emission are observed in data collected from Pareto-optimal solutions. Finally, fuzzy decision making approach is adopted for selecting the best compromise solution.*

Keywords: Virtual Power Plant, Energy Management, Distributed Energy Resource, Emission, Renewable Energy, Electricity Market

1 Introduction

There is a growing concern about emission and global warming today. The electrical industry should consider environmental issues due to greenhouse gas emissions from conventional units and their unsuitable impacts on the environment. Therefore, the evolution of electricity markets is towards the greater dependence on DERs due to their flexible, clean and renewable characteristics [1]. DERs are electric power generators that are directly connected to distribution networks [2]. However, in the current market framework, the minimum amount of bids is required for participation in electricity markets; therefore, only large or medium-sized producers and traders have the opportunity to participate in day-ahead markets [3]. As a result, DERs cannot participate in electricity markets since they are dispersedly located with small capacities. Consequently, they are invisible to system operators and other market players. One suitable solution for this problem is the aggregation of DERs in the VPP framework which improves the visibility and handling of DERs for system and market operators [4].

According to the Europe FENIX project [5]: "A VPP aggregates the capacity of many diverse DERs, it creates a single operating profile from a composite of the parameters characterizing each DER and can incorporate the impact of the network on aggregate DER output ". Due to the fact that VPPs include DERs and participate in electricity markets, the optimal scheduling of these resources and determining the optimal bids of VPP in electricity markets is an important issue [6].

Considerable number of studies has been carried out on the operational scheduling of VPPs, some of which are mentioned here. The optimal day-ahead scheduling of VPP aggregating various kinds of DERs such as renewable and conventional generation units, demand response programs, Combined Heat and Power (CHP) units, and Electrical Energy Storage (EES) systems is presented in [7]. Two-stage stochastic programming is used for modeling the simultaneous energy and reserve scheduling in the aforesaid study. A stochastic framework is proposed in [4] for optimal day-ahead scheduling of a VPP. A modified scenario-based decision making method is presented for modeling the uncertainty of electricity prices, load demand, wind speed and solar radiation. A fuzzy day-ahead scheduling model of VPP is performed in [1]. In order to coordinate profit and reliability, a fuzzy chance constrained programming approach is presented in the aforesaid study. The optimal decisions for commercial VPPs concerning forming a coalition of diverse DERs, bilateral and forward contracting, and pool participation is presented in [3]. The optimum sizing of the main components of combined wind and pumped-storage VPPs is investigated in [8] considering both the investor's perspective, which is the maximization of the return on the investment, as well as the system perspective to increase the penetration of renewable energy resources along with the minimization of costs. An economic operation-based load dispatching strategy of a hybrid system consisting of solar, wind, hydrogen and thermal power systems in the VPP structure is proposed in [9]. The optimal operation of a VPP participating in both day ahead and balancing markets to maximize the expected profit considering risk factors is presented in [10].

Despite many studies in this field, multi-objective economic/emission operational scheduling of VPP has not been considered in any of these studies. Consequently the

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[*] Corresponding Author : H. A. Shayanfar, hashayanfar@gmail.com

VPP energy management considering both profit and emission as objective functions was presented in our previous work in [11] for the first time. In this paper, the authors aim to develop the results of [11] and conduct a more detailed analysis. In fact, the Pareto front is generated with more members by multi-objective PSO and details of each Pareto-optimal solution including the scheduling of DERs (conventional generation units) and the power exchanged with the upstream network are presented. Using the aforesaid details, the impact assessment of profit and emission objectives on the operational scheduling of VPP is carried out. In addition, fuzzy decision making approach is used to select the best compromise solution among Pareto-optimal solutions. It is noteworthy that the VPP under investigation includes various DERs including wind turbines, PhotoVoltaic (PV) modules, CHP systems, heat-only units, and EES systems. Therefore, both electrical and thermal aspects are taken into account. Also, two-stage stochastic programming is used for modeling the optimization problem considering the uncertainty of electricity price, electrical load, solar radiation, and wind speed.

The rest of the paper is organized as follows: Section 2 presents the problem formulation. Section 3 describes the case study. Simulation results and corresponding analysis are provided in Section 4. Finally, Section 5 presents the conclusions of the paper.

2 Problem formulation

In this section, problem formulation including the VPP structure, mathematical modeling, fuzzy decision making process, and the flow chart of the complete procedure of solving the optimization problem are presented.

2.1 Structure of the virtual power plant

The structure of the VPP considered in this paper is the same presented in [11]. The VPP is a set of plants individually connected to radial distribution network as shown in Fig. 1. All resources in the local network of the VPP are assumed to be controlled by the VPP operator. The exchanged power between VPP and the electricity market crosses through line N_p, which is connected to the Point of Common Coupling (PCC) of VPP with the upstream network.

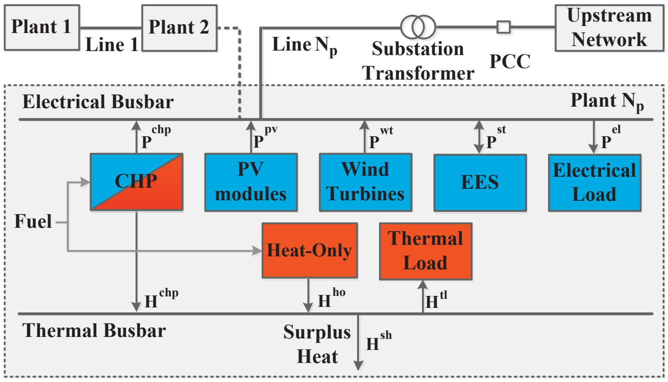

Fig. 1 The structure of each plant.

Each plant consists of electrical and thermal sections. Resources in the electrical section are PV modules, Wind turbines, EES system, and electrical link of CHP unit to supply electrical load. Also, heat-only unit and thermal link of CHP unit are resources in the thermal section for locally supplying the thermal demand.

2.2 Mathematical modeling

Mathematical modeling of DERs as well as profit and emission objective functions is expressed in this section. The nomenclature of our previous work in [11] could be adopted for description of parameters and variables.

2.2.1 Combined heat and power units

This paper models both the first and second type CHP units according to [12]. The operational constraints of CHP units including modeling the convex and non-convex feasible operating regions are given in the aforementioned study. The cost of CHP units is represented by (1). The operational cost is calculated using (2). The startup and shutdown states are also determined by (3) and (4) respectively.

$$C_{t,p}^{chp} = C_{t,p}^{ope} + C_p^{su} \times SU_{t,p}^{chp} + C_p^{sd} \times SD_{t,p}^{chp} \tag{1}$$

$$\begin{aligned} C_{t,p}^{ope}\left(P_{t,p}^{chp}, H_{t,p}^{chp}\right) = a_p \times \left(P_{t,p}^{chp}\right)^2 + b_p \times P_{t,p}^{chp} + c_p \\ + d_p \times \left(H_{t,p}^{chp}\right)^2 + e_p \times H_{t,p}^{chp} + \end{aligned} \tag{2}$$

$$SU_{t,p}^{chp} = V_{t,p}^{chp} \times \left(1 - V_{t-1,p}^{chp}\right) \tag{3}$$

$$SD_{t,p}^{chp} = \left(1 - V_{t,p}^{chp}\right) \times V_{t-1,p}^{chp} \tag{4}$$

2.2.2 Heat-only units

The operational constraint of heat-only units is presented in (5). Production cost of heat-only units which is a non-linear function of thermal output power is expressed in (6) [13].

$$0 \leq H_{t,p}^{ho} \leq H_{max,p}^{ho} \tag{5}$$

$$C_{t,p}^{ho}\left(H_{t,p}^{ho}\right) = \alpha_p \times \left(H_{t,p}^{ho}\right)^2 + \beta_p\left(H_{t,p}^{ho}\right) + \gamma_p \tag{6}$$

2.2.3 Photovoltaic modules

The output power of PV modules which is a function of solar radiation, ambient temperature of the site and the specifications of the modules is calculated using (7)-(11) [4].

$$T_{C_{s,t}} = AT_t + sor_{s,t} \times \left(\frac{N_{OT} - 20}{0.8}\right) \tag{7}$$

$$I_{s,t} = sor_{s,t} \times \left[I_{sc} + K_i \times \left(T_{C_{s,t}} - 25\right)\right] \tag{8}$$

$$V_{s,t} = V_{oc} - K_v \times T_{C_{s,t}} \tag{9}$$

$$FF = \frac{V_{MPP} \times I_{MPP}}{V_{oc} \times I_{sc}} \tag{10}$$

$$P_{s,t,p}^{pv}\left(sor_{s,t}\right) = N_p^{pv} \times FF \times V_{s,t} \times I_{s,t} \tag{11}$$

2.2.4 Wind turbines

The output power of wind turbines which is a nonlinear function of wind speed is determined in (12) as follows [14]:

$$P^{wt}_{s,t,p}\left(v_{s,t}\right) = N^{wt}_p \begin{cases} 0 & v_{s,t} < v^c_{in} \\ P^{wt}_{rated}\left(\dfrac{v_{s,t} - v^c_{in}}{v_{rated} - v^c_{in}}\right)^3 & v^c_{in} \le v_{s,t} < v_{rated} \\ P^{wt}_{rated} & v_{rated} \le v_{s,t} < v^c_{out} \\ 0 & v^c_{out} \le v_{s,t} \end{cases} \tag{12}$$

2.2.5 Electrical energy storage systems

The operational constraints of EES systems are modeled by (13)-(19) [12].

$$0 \le P^{st}_{t,p,ch} \le P^{st}_{p,max,ch} \times b^{st}_{p,ch} \tag{13}$$

$$0 \le P^{st}_{t,p,dch} \le P^{st}_{p,max,dch} \times b^{dch}_{p,dch} \tag{14}$$

$$E^{st}_{p,min} \le SOC^{st}_{t,p} \le E^{st}_{p,max} \tag{15}$$

$$SOC^{st}_{0,p} = E^{st}_{p,initial} \tag{16}$$

$$SOC^{st}_{24,p} = E^{st}_{p,final} \tag{17}$$

$$b^{st}_{p,ch} + b^{dch}_{p,dch} \le 1 \tag{18}$$

$$SOC^{st}_{t,p} = SOC^{st}_{(t-1),p} + \left(\eta^{st}_{p,ch} \times P^{st}_{t,p,ch} - \frac{P^{st}_{t,p,dch}}{\eta^{st}_{p,dch}}\right) \tag{19}$$

2.2.6 Energy not served

If supplying the entire electrical load demand is not possible due to the insufficient production of VPP resources or network constraints, a load curtailment known as Energy Not Served (ENS) is scheduled. The constraint concerning the maximum amount of load curtailment and the cost of ENS are given in (20) and (21) respectively [4].

$$0 \le P^{ens}_{s,t,p} \le P^{ens}_{p,max} \tag{20}$$

$$C^{ens}_{s,t,p}\left(P^{ens}_{s,t,p}\right) = VOLL \times P^{ens}_{s,t,p} \tag{21}$$

2.2.7 Thermal limit of power lines

The constraint imposed on the maximum crossed power through power lines is expressed in (22) [4].

$$\left|P^{line}_{s,t,p}\right| \le P^{line}_{p,max} \tag{22}$$

2.2.8 Power balance

Equations related to electrical and thermal power balances are presented in (23)-(27).

$$P^{eq}_{s,t,p} = P^{chp}_{t,p} + P^{pv}_{s,t,p} + P^{wt}_{s,t,p} + P^{st}_{t,p} - P^{sel}_{s,t,p} \tag{23}$$

$$P^{sel}_{s,t,p} = P^{el}_{s,t,p} - P^{ens}_{s,t,p} \tag{24}$$

$$P^{line}_{s,t,p} = \sum_{i=1}^{p} P^{eq}_{s,t,i} \tag{25}$$

$$P^{grid}_{s,t} = \sum_{i=1}^{N_p} P^{eq}_{s,t,i} \tag{26}$$

$$H^{tl}_{t,p} = H^{chp}_{t,p} + H^{ho}_{t,p} - H^{sh}_{t,p} \tag{27}$$

2.2.9 Objective functions

The maximization of the expected day-ahead VPP Profit is the first objective function expressed in (28). [11].

$$F_{profit} = \max \sum_{s=1}^{N_s} \pi_s \sum_{t=1}^{24} \left\{ \begin{array}{c} -\sum_{p=1}^{N_p} \left\{C^{chp}_{t,p} + C^{ho}_{t,p}\right\} + \\ \left\{ \begin{array}{c} \rho^{em}_{s,t} \times P^{grid}_{s,t} \\ + \sum_{p=1}^{N_p} \left\{ \begin{array}{c} \rho^{ret_e}_t \times P^{sel}_{s,t,p} \\ +\rho^h_t \times H^{tl}_{t,p} - C^{ens}_{s,t,p} \end{array} \right\} \end{array} \right\} \end{array} \right\} \tag{28}$$

The minimization of the expected day-ahead emission is the second objective function presented in (29) [11].

$$F_{emission} = \min \sum_{s=1}^{N_s} \pi_s \sum_{t=1}^{24} \left\{ \begin{array}{c} \sum_{p=1}^{N_p} \left\{E^{chp}_{t,p} + E^{ho}_{t,p}\right\} \\ +E^{grid}_{s,t} \end{array} \right\} \tag{29}$$

The total emission per hour by CHP units, heat-only units, and grid generation system are determined by (30)-(32) respectively [11].

$$E^{chp}_{t,p} = \left({NO_X}^{chp} + {SO_2}^{chp} + {CO_2}^{chp}\right) \times P^{chp}_{t,p} \tag{30}$$

$$E^{ho}_{t,p} = \left({NO_X}^{ho} + {SO_2}^{ho} + {CO_2}^{ho}\right) \times H^{ho}_{t,p} \tag{31}$$

$$E^{grid}_{s,t} = \left({NO_X}^{grid} + {SO_2}^{grid} + {CO_2}^{grid}\right) \times max\left\{-P^{grid}_{s,t}, 0\right\} \tag{32}$$

2.3 Fuzzy decision making approach

Fuzzy sets are used in this paper to select a compromise solution among Pareto-optimal solutions according to [15]. A linear membership function for each of the objective functions is calculated in (33).

$$\mu^k_i = \begin{cases} 1, & F^k_i \le F^{min}_i \\ \left[\dfrac{F^{max}_i - F^k_i}{F^{max}_i - F^{min}_i}\right], & F^{min}_i \le F^k_i \le F^{max}_i \\ 0, & F^k_i \ge F^{max}_i \end{cases} \tag{33}$$

The membership function is normalized as follows:

$$\mu^k = \frac{\sum_{i=1}^{N_F} \omega_i F_i^k}{\sum_{k=1}^{N_{rep}} \sum_{i=1}^{N_F} \omega_i F_i^k} \tag{34}$$

Where i is the set of objective functions, ranging from 1 to N_F and k is the set of Pareto-optimal solutions ranging from 1 to N_{rep}. Weight value of the ith objective function is denoted by ω_i. Also, μ_i^k and μ^k are linear and normalized membership functions, respectively. Value of the ith objective function in the kth Pareto-optimal solution is illustrated by F_i^k. In addition, F_i^{max} and F_i^{min} are the maximum and minimum value of the ith objective function.

It is noteworthy that the amount of weights (ω_i) are assigned based on the economic constraints related to the operation of the system and regulatory restrictions concerning emission. The best compromise solution is the Pareto-optimal solution having the maximum membership function.

2.4 Stochastic optimization

The procedure of solving the scheduling problem is illustrated in Fig. 2. The optimization module initially receives deterministic and uncertain input parameters as well as technical constraints and then generates Pareto-optimal solutions. After receiving weight values, fuzzy decision making module determines the optimal scheduling of DERs and biding strategy in the day-ahead market.

3 Case study

The proposed method for multi-objective energy management is applied to a VPP consisting of four plants, each plant having the same structure as Fig. 1. The energy management is performed for a 24-h period with 1-h time-step. A precise code including 288 real variables is developed to achieve the minimum runtime.

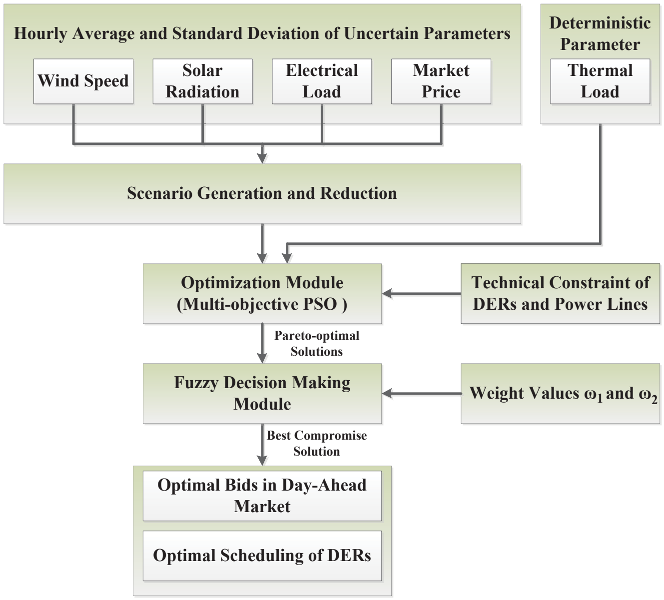

Fig. 2 Complete procedure of solving the optimization problem.

The number of particles and repository members for multi-objective PSO algorithm are considered to be 100 and 250, respectively. The hourly average values of electrical and thermal loads (Fig. 3) as well as the VPP's retail rates are according to [11]. The hourly electricity price of power market is taken from [16]. 80% of the electricity retail rate is considered for the sales price of heat to customers. Scenario generation and reduction method used is well described in [17]. Seven scenarios are generated considering standard deviation of uncertain parameters equal to 10%. The operational parameters of CHP units are taken from [12]. The input data for PV modules is according to [4]. The required data for wind turbines is given in [18]. As regards solar radiation, the monthly average of data for each hour in august, which is provided in [19], is considered as the input data. The data concerning wind speed and ambient temperature are presented in [20]. The technical parameters of heat-only units and EES systems are taken from [11]. Emission factors related to gas-fired heat-only units are provided in [21]. Also, the emission factors for CHP units and grid generation system are available in [12].

4 Simulation results and analysis

The multi-objective energy management of VPP results in generation of Pareto-optimal solutions illustrated in Fig. 4. The Pareto front consists of 250 repository members shown in yellow circles. It is clear that emission goes up with the increase in the VPP profit (Fig. 4). Twenty five members of the repository, shown in red stars, are selected for analysis of the results. Details of the selected members including the production of DERs (CHP and heat-only units), the amount of power exchanged with the upstream network, expected day-ahead VPP profit, expected day-ahead emission, and membership functions are presented in Table 1. Both profit and emission are decreased from the top to the bottom of Table 1 (the sixth and seventh columns). The results indicate about 60% reduction in profit and around 50% decrease in emission in the last Pareto-optimal solution (#25) compared to the first one (#1).

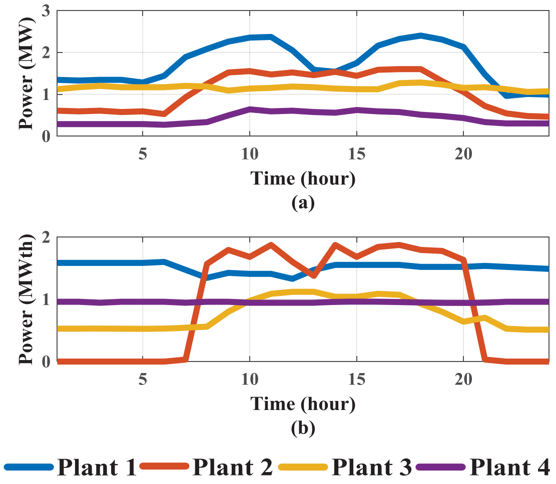

Fig. 3 The (a) electrical and (b) thermal load demands.

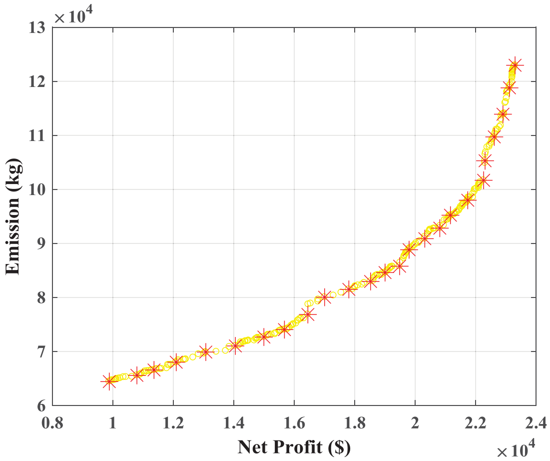

Fig. 4 The Pareto-optimal solutions.

Considering ω_1 and ω_2 equal to 0.7 and 0.3 respectively results in the selection of the sixth Pareto-optimal solution as the best compromise solution using the fuzzy decision making approach (the value of profit is considered with negative sign in (33)). In order to give a better view on results, the electrical power balance in the local network of VPP (considering the total power of four plants) is illustrated in Fig. 5 for three Pareto-optimal solutions representing the maximum profit (#1), the best compromise solution (#6), and the minimum emission (#25). The first (#1) and the last (#25) Pareto-optimal solutions whose results are presented in Fig. 5(a) and Fig. 5 (c) respectively, are obtained by the single-objective VPP energy management using PSO algorithm (the convergence curves and statistical results of PSO algorithm are available in [11]).

In Fig. 5 (a), the VPP sells electricity at peak price periods to the electricity market like a real power plant and purchases electricity during periods with low electricity price like a consumer to increase its profit. However in Fig. 5 (c), the VPP supplies demand with DERs in its territory in order to decrease emission by not purchasing electricity from grid generation system having high emission factors.

As regards the power exchanged between the VPP and the electricity market (the fifth column of Table 1), the power drops with the decrease in profit objective function. This is due to the fact that the VPP gains profit by selling power to the electricity market during periods with high electricity price. Similarly, the VPP reduces its cost by purchasing electricity during periods with low electricity price. Consequently, the drop in the power exchanged with the upstream network results in lower profits during peak price periods and higher costs during low price periods. Also, the power declines with the decrease in emission for two reasons. First, the committed power plants in the main grid have higher emission factors compared to DERs of the VPP. Therefore, supplying the load demand by VPP resources during periods with low electricity price rather than purchasing electricity from the main grid will reduce the emission. It is also obvious that reducing the sales of electricity to the electricity market will result in lower power production from VPP resources and lower emission. The results presented in Fig. 5 also confirm the above discussion, since the power exchanged with the electricity market is decreased from Fig. 5 (a) to Fig. 5 (c).

If we look at the second column, the electrical output power of CHP units is declined from the top to the bottom of Table 1 with the decrease in profit and emission. The reason is that the reduction in the electrical output power of CHP units during peak price periods results in lower profits (due to the reduced sales to the electricity market) and lower emission.

Table 1 Specifications of the Pareto-optimal solutions.

Pareto Solutions	CHP Units (Electrical) (MW/day)	CHP Units (Thermal) (MWth/day)	Heat-Only Units (MWth/day)	Power Exchanged with the Electricity Market (MW/day)	Net Profit ($/day)	Emission (kg/day)	μ_1	μ_2	μ
1	107.538	29.726	70.020	66.035	23,303	122,963	1	0	0.0461
2	105.088	33.324	67.337	60.820	23,118	118,789	0.986	0.071	0.0469
3	105.134	40.860	59.680	56.987	22,902	113,908	0.970	0.155	0.0478
4	104.396	46.447	54.107	53.349	22,615	109,716	0.949	0.226	0.0482
5	99.462	48.286	52.699	48.003	22,310	105,298	0.926	0.302	0.0487
*6	101.257	53.575	47.203	43.886	22,262	101,682	0.923	0.364	0.0497
7	99.952	58.692	42.808	40.419	21,738	97,990	0.883	0.427	0.0491
8	96.968	62.047	40.071	38.513	21,165	95,218	0.841	0.474	0.0481
9	96.908	65.622	37.631	35.643	20,814	92,822	0.815	0.515	0.0477
10	93.120	64.221	37.809	33.718	20,317	90,878	0.778	0.548	0.0467
11	95.754	70.728	33.280	31.769	19,798	88,830	0.739	0.583	0.0456
12	93.906	72.155	30.309	28.555	19,484	85,782	0.715	0.635	0.0455
13	94.065	71.221	31.364	25.382	19,003	84,605	0.680	0.655	0.0443
14	91.815	72.041	30.399	24.109	18,524	82,962	0.644	0.683	0.0432
15	87.479	71.939	31.215	22.605	17,806	81,492	0.590	0.709	0.0412
16	86.951	72.666	29.977	21.128	17,004	80,039	0.531	0.733	0.0389
17	86.930	72.533	28.375	16.104	16,451	76,851	0.489	0.788	0.0381
18	85.933	76.615	24.948	13.420	15,676	74,051	0.432	0.836	0.0364
19	84.659	77.805	24.000	12.107	14,996	72,678	0.381	0.859	0.0345
20	82.474	77.816	24.115	10.041	14,054	71,030	0.311	0.887	0.0319
21	80.594	76.615	24.340	8.568	13,075	69,897	0.238	0.907	0.0289
22	79.645	77.219	23.609	5.626	12,097	68,020	0.165	0.939	0.0261
23	78.529	76.358	23.519	3.289	11,363	66,580	0.110	0.963	0.0241
24	77.376	76.942	23.032	2.221	10,797	65,583	0.68	0.980	0.0225
25	75.793	76.061	23.738	0	9,884	64,432	0	1	0.0198

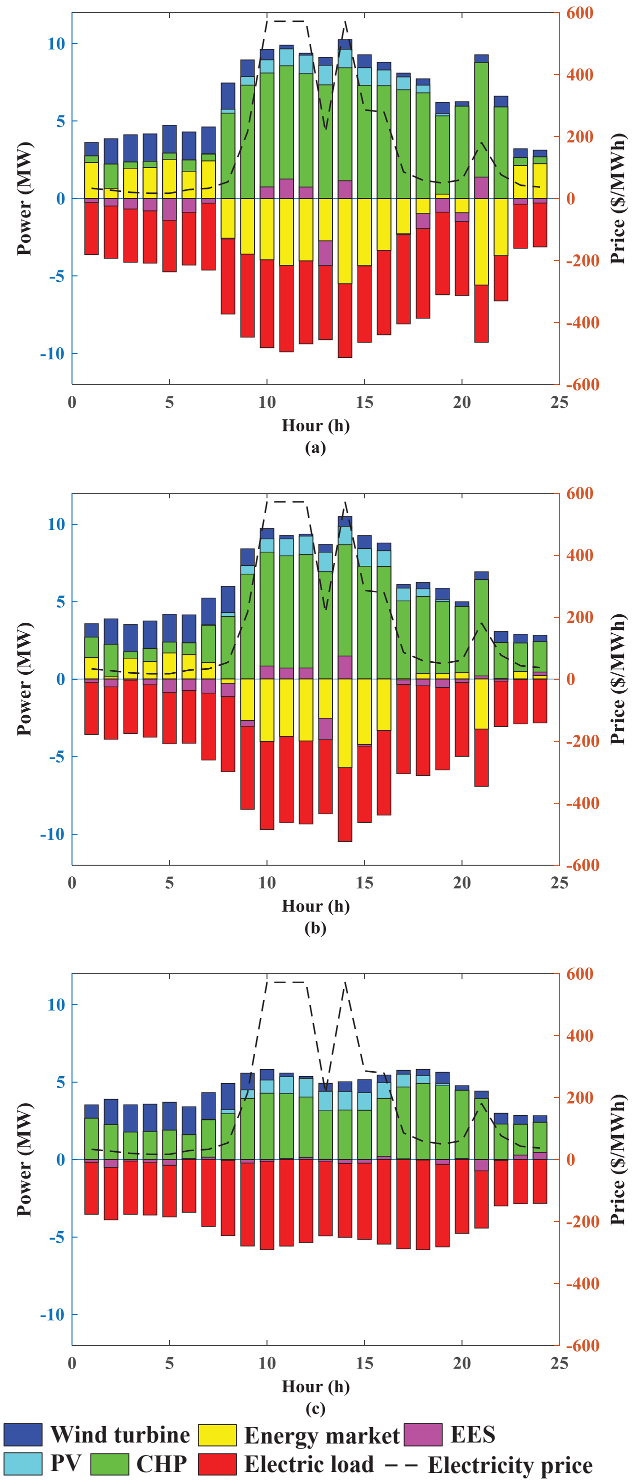

Fig. 5 Electrical power balance in the local network of the VPP for Pareto-optimal solution (a) #1, (b) #6, and (c) #25.

Although the lower production of CHP units during low price periods results in lower costs and higher emission (since grid generation system have higher emission factors compared to the DERs of the VPP), the total electrical output power of CHP units during the 24-h scheduling period declines with the decrease in profit and emission.

On the other hand, the thermal output power of CHP units increases from the top to the bottom of the third column of Table 1 with the decrease in profit and emission objectives. This is due to the fact that the thermal output power of CHP units does not increase emission objective function in (29). Consequently, supplying the thermal load by CHP units rather than heat-only units will result in lower emission. Therefore, heat-only units will have a smaller share in supplying thermal load demand as shown in the fourth column of Table 1.

Using the fuzzy decision making method and selecting the best compromise solution gives VPP operator the opportunity of adopting a moderate scheduling of DERs considering both profit and emission aspects (Fig. 5 (b)).

5 Conclusions

In this paper, the day-ahead economic/emission energy management of a VPP was performed considering the uncertainty of renewable generations, load and price. The multi-objective PSO was used to solve the nonlinear and non-convex optimization problem and to generate the Pareto-optimal solutions. The impact assessment of profit and emission objectives on the operational scheduling of VPP was conducted using the specifications of Pareto-optimal solutions (Table 1). The results indicate that the power exchanged between the VPP and the electricity market drops with the decrease in profit and emission objective functions. This is due to the fact the decrease in the power exchanged with the electricity market results in higher costs during low price periods and lower profit during peak price periods. Also, the electrical output power of CHP units rises with the increase in profit and emission objectives. This is because the VPP can sell more electricity to the electricity market to gain profit by increasing the electrical output power of CHP units during peak price periods. The rise in the electrical power of CHP units will also increase the emission. On the other hand, the thermal output power of CHP units increases with the decrease in the profit and emission objective functions. As a result, the contribution of heat-only units to supplying the thermal load demand will decline with the decrease in the profit and emission. It is also noteworthy that about 60% reduction in profit and around 50% decrease in emission were observed in the specifications of Pareto-optimal solutions. Finally, using the fuzzy decision making approach helps VPP operator with selecting a compromise solution and adopting a moderate scheduling of DERs considering both the profit and emission aspects. Implementation of demand response programs and more grid constraints such as reactive power consideration are contributions of our future work.

Appendix

The scheduling of CHP and heat-only units for the compromise solution (#6) is presented in Table 2. The scheduling results for the maximum profit (#1) and the minimum emission (#25) cases are also available in [11].

Table 2 Optimal scheduling of CHP and heat-only units for the best compromise solution (#6).

Hour	$P_{t,p}^{chp}(MW)$				$H_{t,p}^{chp}\ (MWth)$				$H_{t,p}^{ho}\ (MWth)$			
	Plant 1	Plant 2	Plant 3	Plant 4	Plant 1	Plant 2	Plant 3	Plant 4	Plant 1	Plant 2	Plant 3	Plant 4
1	0.4367	0	0.8881	0	0.6580	0	0.7052	0	0.9260	0	0	0.9600
2	0.8901	0	1.2169	0	1.1711	0	0.5290	0	0.4129	0	0	0.9600
3	0.4065	0	0	0	0.7415	0	0	0	0.8425	0	0.5280	0.9440
4	0.8464	0	0	0	1.1330	0	0	0	0.4510	0	0.5280	0.9600
5	0.7060	0	0	0	1.0138	0	0	0	0.5702	0	0.5280	0.9600
6	0.7626	0	0	0	0.7504	0	0	0	0.8496	0	0.5280	0.9600
7	1.0863	0	0	1.3218	1.3233	0	0	0.9376	0.1487	0.0320	0.5440	0.0064
8	0.8710	1.0916	1.0579	1.0168	1.1560	1.3456	0.7170	0.7654	0.1880	0.2224	0	0.1946
9	0.8162	1.0743	2.4127	2.4700	1.1079	1.1087	0.2035	0	0.3161	0.6833	0.5965	0.9600
10	1.2566	1.2343	2.3910	2.4693	0.3333	0.4806	0.3765	0.0035	1.0747	1.1994	0.5995	0.9405
11	1.2580	1.1524	2.3658	2.4629	0.2211	1.0220	0.5489	0.0102	1.1869	0.8500	0.5391	0.9338
12	1.2580	1.2154	2.3756	2.4699	0.2149	0.5984	0.5296	0	1.1131	1.0016	0.5904	0.9437
13	1.2347	0.9481	2.2752	2.4693	0.2719	1.2232	1.0939	0.0029	1.2000	0.1528	0.0261	0.9411
14	1.2210	1.1000	2.3913	2.4687	0.5688	1.3543	0.3476	0.0042	0.9832	0.5177	0.6000	0.9558
15	1.2341	1.2295	2.3506	2.4698	0.4391	0.4818	0.5694	0	1.1129	1.1982	0.4706	0.9590
16	1.2436	1.1768	2.3776	2.4698	0.3902	0.7085	0.5170	0	1.1618	1.1315	0.5710	0.9592
17	0.8698	1.0993	2.0342	1.0393	1.0932	1.3397	1.3121	0.9659	0.4588	0.5323	0	0
18	0.8444	1.0896	2.2261	0.8195	1.0859	1.3453	0.9285	1.0080	0.4341	0.4467	0	0
19	1.1159	0.7724	1.9248	0.8404	1.0050	0.8143	0.8055	0.9706	0.5150	0.9617	0	0
20	1.0733	1.0843	0.9589	1.1689	1.2468	1.3347	0.8722	0.9006	0.2732	0.2973	0	0.0434
21	1.1848	0.7253	2.1201	2.1927	0.5563	0.0701	0.5502	1.0844	0.9797	0	0.1538	0
22	0.8597	0	0	1.4907	1.1464	0	0	0.9245	0.3736	0	0.5280	0.0355
23	0.9614	0	0	0.8695	1.2346	0	0	1.0133	0.1694	0	0.5120	0
24	1.1020	0	0	0.8492	1.3262	0	0	0.9597	0.1618	0	0.5120	0

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