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Electrical energy management in unbalanced distribution networks using virtual power plant concept

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ABSTRACT

This paper integrates different developed optimization algorithms based on modification of the big bang big crunch method for virtual power plant realization. The proposed algorithms aim to manage the electrical energy in unbalanced distribution networks in order to minimize the purchased energy from the grid. This goal is achieved through the optimal placement of renewable based distributed generators, optimal scheduling of the controllable loads and optimal operation of energy storage elements. The proposed algorithms are implemented in MATLAB environment and tested on the IEEE 37-node feeder. The results show great reduction in the purchased energy from the grid and the subsequent discussions emphasize the significance of using the virtual power plant concept in managing the electrical energy.

1. Introduction

Virtual power plant (VPP) is a recent rapidly growing concept that has many definitions; all these definitions agree upon the fact that VPP is an aggregation of distributed generation (DG, small generating units connected to the distribution network) units of different technologies in order to operate as a single power plant that has the ability to control the aggregated units and to manage the electrical energy flow between these units in order to obtain better operation of the system [1–6]. From the authors perspective VPP can be viewed as “A concourse of dispatchable and non dispatchable DGs, energy storage elements and controllable loads accompanied by information and communication technologies to form a single imaginary power plant that plans, monitors the operation, and coordinates the power flows between its component to minimize the generation costs, minimize the production of greenhouse gases, maximize the profits, and enhance the trade inside the electricity market”.

VPP consists of the three main components, distributed energy resources (DER), energy storage elements (ESEs) and information and communication systems. DER can be either distributed generators or controllable loads connected to the network, ESEs can store energy during off-peak periods and feed it during the peak periods and the information and communication systems manages the operation of other VPP components through communication technologies in bidirectional ways.

The optimal VPP operation aims at enhancing its operation and minimizing the cost of its produced energy. VPP optimization methodology depends on the power system under study; either if it is new or existing. For a newly-established power system, VPP has the ability to choose the capacity and location of the DG units and ESEs, and the locations of the loads to be controlled and the appropriate control strategies and schedules. On the other hand for existing power systems, these options are limited as the location and size of the DG units and ESEs, and the locations of the controllable loads are pre-determined. The studies slanted toward the optimization of the VPP operation [7–23] can be categorized into three groups:

1) DG units' optimal sizing and siting [7–15]: Researchers investigated various optimization techniques to determine the optimal location and size of DG in order to reduce power loss and improve the voltage profile of the power system. Similarly, VPP optimization can be carried out through optimal placing of stochastic DG units (wind and photovoltaic). Other studies were performed to select the optimal capacity of a conventional power plant used in collaboration with DG units as well as purchasing energy from the electricity market to supply the required VPP energy.

   The optimization methods used for optimal sizing and siting of DG units could be analytical [7–9], numerical [10–12] and heuristic [13–15].

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2) ESEs optimal sizing and siting [16–20]: Optimal sizing and siting of ESEs helps in reducing power loss, improving voltage profiles, and in optimizing the generation of stochastic DGs.
3) Optimal load control scheduling [21–23]: The VPP has the authority to control or even to interrupt the loads according to their importance in order to optimize its operation.

This paper presents three optimization algorithms based on modification of the big bang big crunch (BB–BC) method [24] for optimal placement of renewable based DGs, optimal sizing of ESEs and optimal load control scheduling. The proposed algorithms are integrated together in order to minimize the energy purchased from the grid which realize the VPP concept. The proposed algorithms are implemented in MATLAB and tested on the IEEE 37-node feeder. The results emphasize the significance of using the virtual power plant concept in managing the electrical energy.

2. Problem statement

The optimization problem under study can be stated as:

GIVEN: the input data comprise the distribution feeder structure, feeder loads values, load types, and available renewable based DGs power schedule.

Objective functions: the objective function is to minimize the annual energy purchased from grid using Eq. (1)

$$\text{Minimize} \sum_{\mathrm{h}=1}^{96} P_{sub,\mathrm{h}} \times 90 \tag{1}$$

Where: $P_{sub,\mathrm{h}}$ is the active power purchased from substation at certain hour h. The 96 value represents the total number of hours of the typical day model of the four seasons (4 × 24 h), the 90 value represents the number of repetition of the typical day model of the four seasons (3 months for each season × 30 days per season).

REQUIRED: to determine exactly the required (optimal) renewable based DG power schedule and location, optimal load control schedule and optimal size and operation schedule of the ESEs for the sake of minimizing the energy purchased from substation without violating the following system constraints:

- Voltage limits: voltage at each bus should be within a permissible range usually:

$$0.95\ \text{p.u.} \le V \le 1.05\ \text{p.u.} \tag{2}$$

- Lines thermal limit (line Ampacity): it represents the maximum current that the line can withstand at certain DG penetration, exceeding this value leads to melting of the line.

$$I_{flow} \le I_{Thermal} \tag{3}$$

- Power balance: the sum of input power should be equal to the sum of output active power in addition to the active power loss. The input power may include the DG active power, the ESEs power and the active power supplied by the utility. The active output power is the sum of loads active power.

$$P_{sub} + P_{ESE} + \sum P_{DG} = \sum P_{loads} + P_{loss} \tag{4}$$

ASSUMPTIONS: The following assumptions are made.

- All the renewable DG units are working at a unity power factor.
- All buses in the system under study are subjected to the same meteorological conditions.
- All loads participating in the load control program may be subjected to 10% reduction at any hour of the day.
- All loads are scaled by multiplying them by load scaling factor obtained from the modeling strategy presented in Section 3.
- Load control interval is exactly one hour (i.e. each load is controlled once per day).
- Controlling multiple loads at the same time interval is permitted.
- The energy can be fed back to the substation (i.e. grid).
- Any day model for each season starts at 12:00 pm

APPROACH: apply the modified BB–BC method to solve the optimization problem and find the optimal location and power schedule of DGs, optimal load control schedule and optimal charging and discharging schedule of ESEs in order to minimize the energy purchased from substation.

3. VPP components modeling

3.1. Renewable based DGs and load modeling

The model presented in Ref. [25] is used. This model considers the stochastic nature and dependence of renewable based DG and system demand. This probabilistic model is based on Monte Carlo method and diagonal band copula according to three years of historical meteorological and system demand data. The results of this model are the most likelihood values of the PV power, wind power and system demand for the 96 h represent the four season's typical day model.

3.2. Energy storage elements modeling

ESE model is described using Eqs. (5) and (6) subjected to the constraints from Eqs. (7) to (10)

$$\mathit{Discharge}:\ E(t+1) = E(t) + P(t).\Delta t/\eta_d,\ p(t) = -ve \tag{5}$$

$$\mathit{Charge}:\ E(t+1) = E(t) + P(t).\Delta t.\eta_c\ ,\ p(t) = +ve \tag{6}$$

Subjected to power limits:

$$0 \le P(t).\eta_c \le P_{\max} \tag{7}$$

$$-P_{\max} \le P(t)/\eta_d \le 0 \tag{8}$$

Stored energy limits:

$$0 \le E(t) \le E_{\max} \tag{9}$$

Starting and ending limits:

$$E(0) = E_{final} \tag{10}$$

Where $E(t)$ is the energy stored in the ESE at time t. $P(t)$ is the power of the ESE output at time t. Δt is the time duration of each interval and equals to 1 h. η_d and η_c are the discharge and charge efficiency respectively. $P_{\max}$ is the maximum discharging or charging rates. $E_{\max}$ is the maximum energy stored in the ESE respectively. For the energy balance of the ESE, the final stored energy inside the ESE (E_{final}) at the end of period of study is set to be the same as initial stored energy inside the ESE ($E(0)$).

4. Methodology

The electrical energy is managed within the VPP to achieve the required objective using the following procedure:

1 Optimal allocation of RES in order to achieve the required objective (i.e. minimize the energy purchased from grid).
2 Determination of the optimal load control schedule required to minimize the purchased energy while the RES are connected to their optimal locations.
3 Determination of the optimal power schedule of the RES, considering them dispatchable, required to minimize the purchased energy.

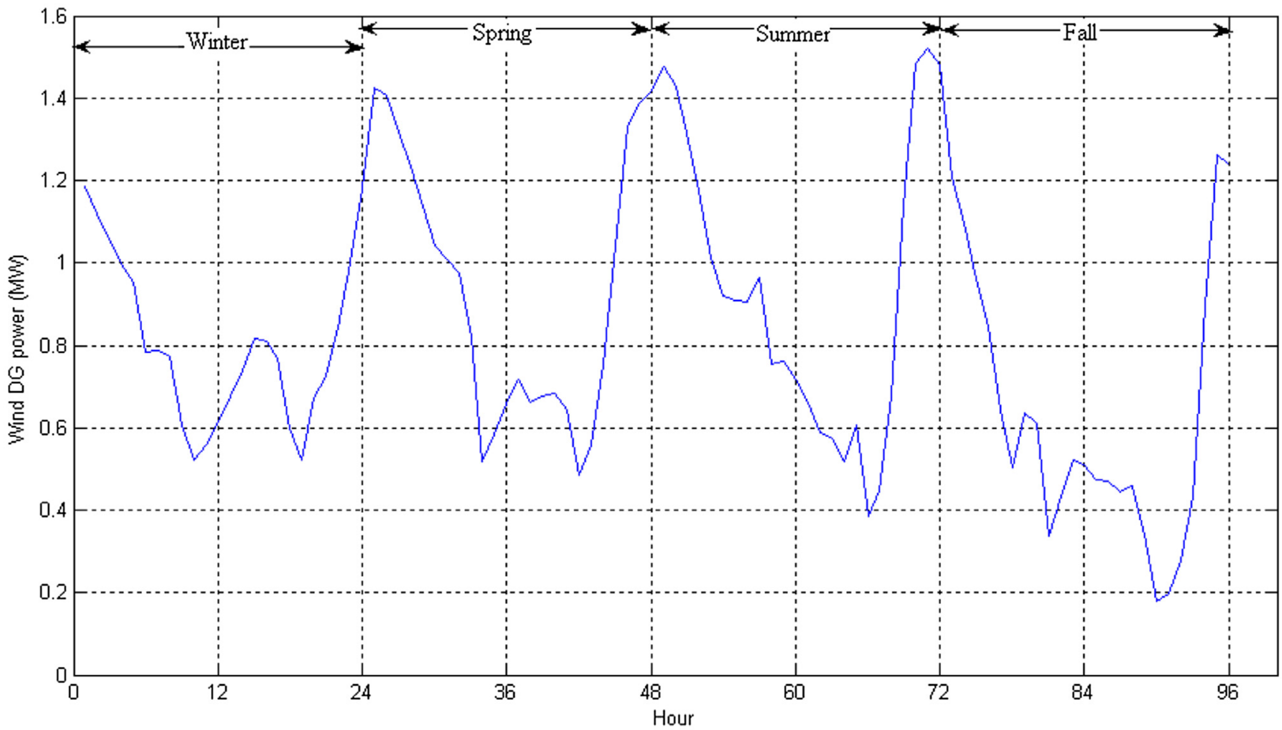


Fig. 1. Four seasons typical day model of aggregated wind power of the two wind turbines.

Table 1
Characteristics of the wind turbines available.

Features Rated power	Turbine 1 1 MW	Turbine 2 1.1 MW
Cut in speed (m/s)	4	4
Rated speed (m/s)	13	12
Cut out speed (m/s)	21	20

4 Using the ESEs to minimize the differences between the optimal power schedule (obtained from previous step) and actual power schedule of the RES (obtained from the model presented in Ref. [25]).

4.1. Optimal allocation of the RES for energy minimization

The proposed optimization algorithm aim to determine the optimal locations of renewable based DGs in order to minimize the energy purchased from grid.

The supervised BB–BC is used for specifying the optimal locations of renewable DGs and the optimal hourly power schedule of dispatchable distributed generators. The proposed method is discussed in the following step by step procedure.

The following step by step procedure summarizes the proposed method.

1) Generate randomly the initial values of the locations for the two renewable DGs (wind DG and PV DG).
2) Calculate the annual energy purchased from grid corresponding to all initial DGs locations and the seasonal hourly power schedule of the wind DG or the PV DG by running unbalanced load flow for the 96 h.
3) Select the best two DG locations that achieve minimum annual energy purchased.
4) Update the DG locations using Eq. (11). The best DG location is kept as a one of the new system variables, the DG locations are rounded to the nearest integer.

$$loc_{new} = loc_{best} + \frac{up_{loc} \times Randn}{it^2} \tag{11}$$

Where loc_{new} is the new candidate DG location, loc_{best} is the best DG location during the iteration, up_{loc} is the maximum values of DGs' locations, $Randn$ is a normally distributed random number and it is the iteration step.

5) Repeat steps (2–4) until the convergence criteria is met, the convergence is considered achieved when more than 50% of the DGs' locations are converged to a certain value.

4.2. Optimal load control for energy minimization

The proposed optimization algorithm aims to determine the optimal load control schedule in order to minimize the energy purchased from grid. The proposed method is discussed in the following step by step procedure:

Table 2
Characteristics of the PV module available.

Module characteristics	Watt peak (W)	Open circuit voltage (V)	Short circuit current (A)	Voltage at maximum power (V)	Current at maximum power (A)	Voltage temperature Coefficient (mV/°C)	Current temperature Coefficient (A/°C)	Nominal cell operating temperature (°C)
Features	53	21.7	3.4	17.4	3.05	88	1.5	43

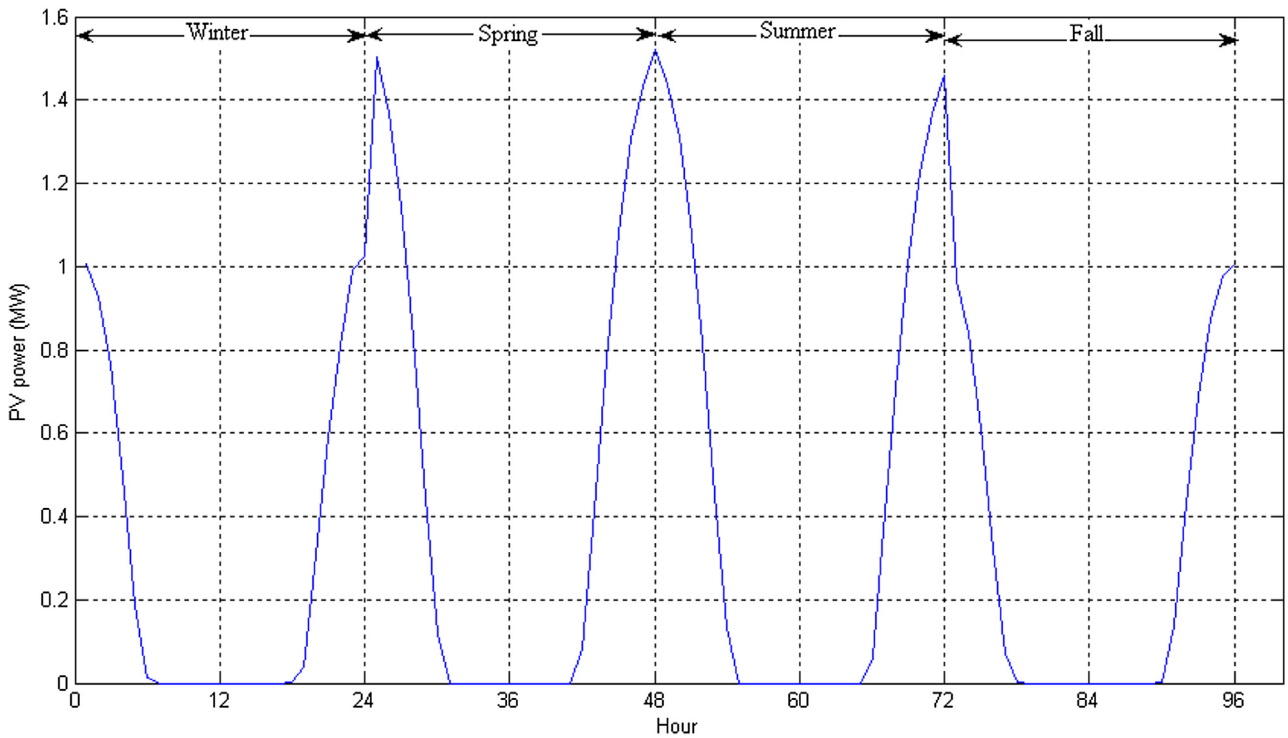


Fig. 2. Four seasons typical day model of output power of 40,000 PV modules.

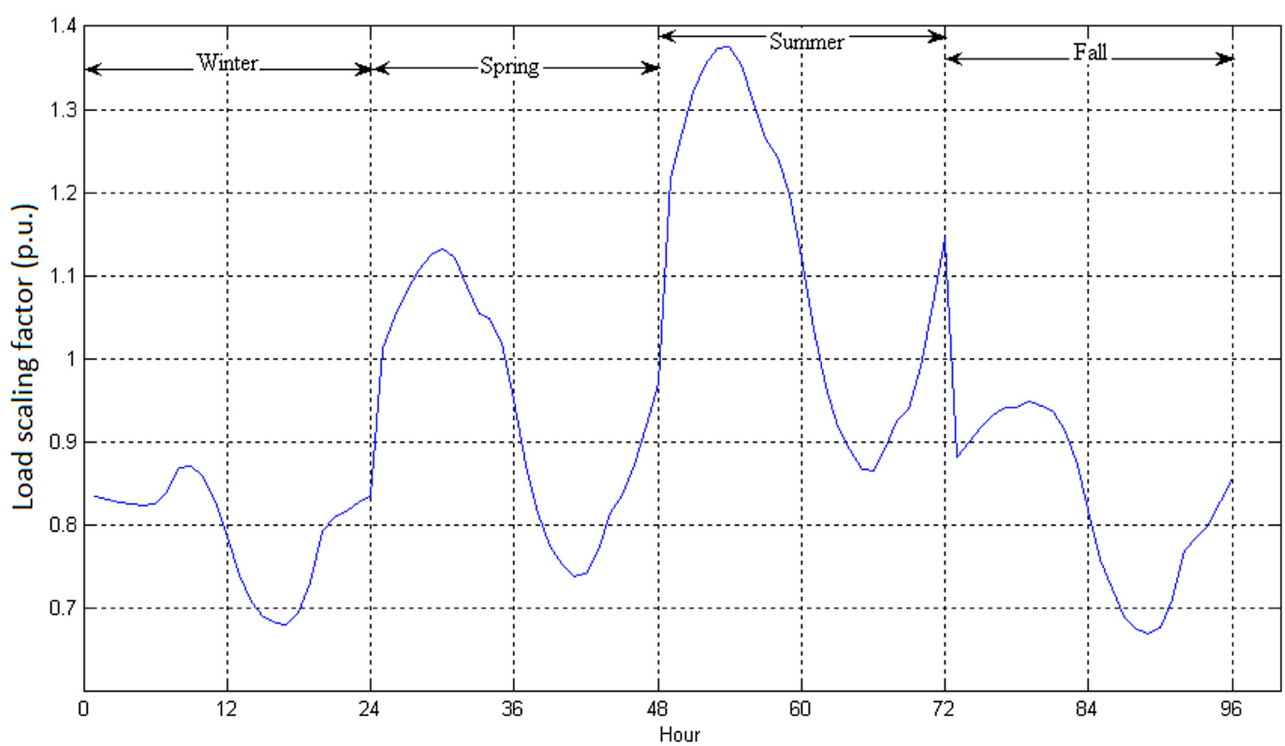


Fig. 3. Four seasons typical day model of normalized system demand profile (load scaling factor).

Table 3
Optimal location for renewable DGs for energy minimization.

Test case	Wind based DG optimal location	Solar based DG optimal location	Energy purchased from substation (MWh)	Energy supplied to substation (MWh)
Base case	–	–	14315.4	0
RES integrated	25	7	5282.3	1485.4

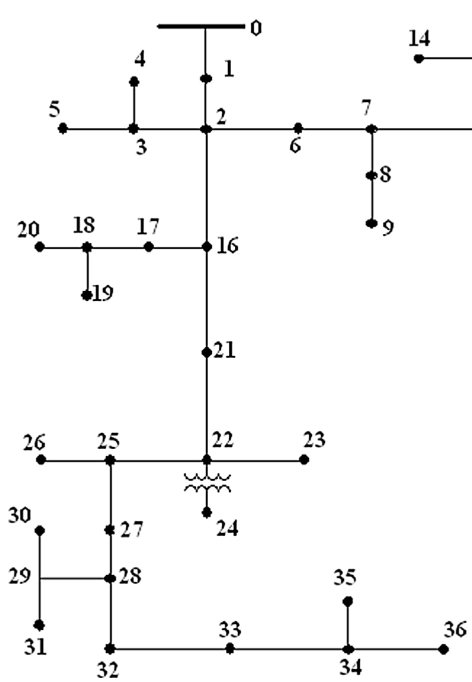


Fig. 4. Renumbered IEEE 37-node feeder.

1) Start with a certain season.
2) Define a set of the loads participating in load control program (i.e. #*NL* number of loads).
3) Generate randomly the initial values of the system variables (i.e. load locations to be controlled and hours).
4) Perform unbalanced load flow to calculate the energy reduction (purchased from substation) from the base case (i.e. where no control is done) corresponding to all initial variables (controllable loads and hours).
5) Select the best controllable load and hour that achieve maximum energy reduction.
6) Update the load locations and hours using Eqs. (12) and (13). Keep the best controllable load and hour as one of the new system variables. Round the load locations and hours to the nearest integer. The new load locations and hours are upper and lower bounded. Moreover, the load locations are bounded to the list of controllable loads defined in Step (2).

$$lloc_{new} = lloc_{best} + \frac{up_{lloc} \times Randn}{it^2} \quad (12)$$

$$h^{new} = h^{best} + \frac{24 \times Randn}{it^2} \quad (13)$$

Where: $lloc_{new}$ and h^{new} are the new candidates load locations and hours respectively, $lloc_{best}$ and h^{best} are the best load locations and hours during the iteration and up_{lloc} is the maximum value of load locations.

7) Repeat Steps (3)–(6) until the convergence criterion is met. The convergence is considered achieved when more than 50% of the load locations and hours converged to the same values.
8) Remove the load location determined from Step (7) from the list of controllable loads defined in Step (2). Reduce this load by 10% during the hour obtained from Step (7).
9) Repeat Steps (2)–(8) to encounter all controllable loads.
10) Repeat for other seasons.

Table 4
List of controllable loads.

Feeder	IEEE 37 nodes feeder
Controllable loads	1, 4–6, 8–10, 12, 14, 15, 17, 18–21, 23, 26–28, 30–33, 35, 36

Table 5
Optimal control schedule for the four seasons.

Winter		Spring		Summer		Fall	
Load	Hour	Load	Hour	Load	Hour	Load	Hour
1	9	1	6	1	7	1	7
5	24	14	6	5	6	19	7
32	24	32	6	14	6	32	7
14	9	5	6	32	6	14	7
10	24	10	6	33	6	10	7
4	9	33	5	35	6	33	7
19	9	4	6	19	6	5	7
6	9	19	6	10	6	35	7
33	8	6	6	4	6	4	7
35	8	35	6	6	6	6	7
31	9	31	6	31	6	31	7
9	9	27	6	27	6	27	7
27	9	21	6	21	6	9	7
21	24	23	6	9	6	21	7
23	24	28	6	23	6	23	7
28	9	9	6	28	6	28	6
26	8	17	6	26	6	26	7
36	9	26	6	36	6	36	7
17	9	12	6	17	6	17	7
12	9	36	5	12	6	12	7
18	9	18	6	18	6	18	7
20	9	20	6	20	6	20	7
15	24	15	5	15	6	15	7
30	9	30	6	30	6	30	7
8	9	8	6	8	6	8	7

Table 6
Purchased energy reduction due to load control.

Reduction in energy purchased from substation (MWh)				
Winter	Spring	Summer	Fall	Annual
14.0199	18.1650	22.1698	15.3100	69.6647

Table 7
Optimal energy purchased from substation using VPP concept.

Test case	Energy purchased from substation (MWh)				
Season	Winter	Spring	Summer	Fall	Annual
Base case	3074.9	3667.1	4357.3	3216.1	14315.4
RES only integrated	954.8	1155.8	1693.0	1478.7	5282.3
Using VPP concept	669.3	533.4	1263.7	1216.0	3682.4

4.3. *Optimal power schedule of RES for energy minimization*

In order to obtain the required power schedule, the RES are considered dispatchable and placed at the optimal locations determined from A. The objective function is to minimize the energy purchased from substation; this objective is achieved by determination of optimal power schedule of the DGs required to reduce the substation power to zero at each hour. The proposed method is discussed in the following step by step procedure.

1) Start with first hour (h = 1).
2) Randomly generate the initial values of the system variables (DGs active powers).
3) Perform unbalanced load flow to calculate the substation power corresponding to all initial DGs' powers.
4) Select the best DG power that achieve minimum substation power.

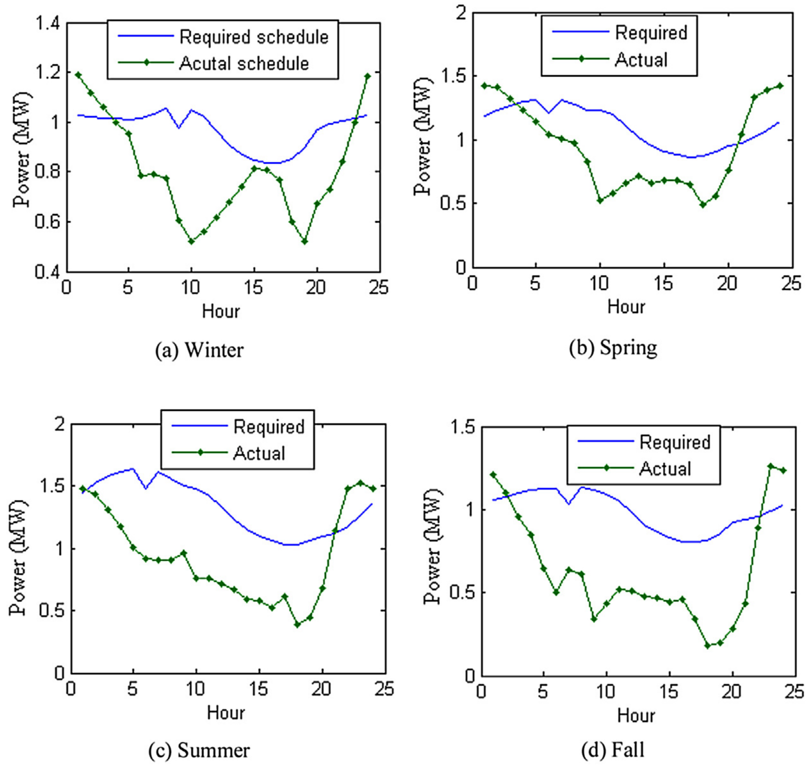


Fig. 5. Optimal and actual power schedules for the four seasons, wind.

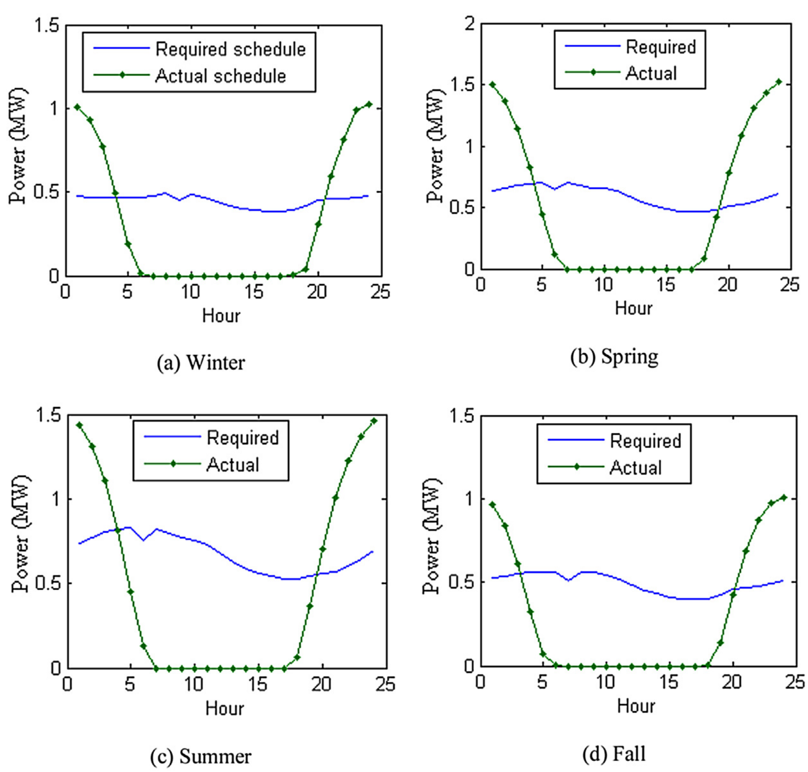


Fig. 6. Optimal and actual power schedules for the four seasons, PV.

5) Update the DGs powers using Eq. (14).

$$P_g^{new} = P_g^{best} + \frac{up_p \times Randn}{it^2} \quad (14)$$

Where: p_g^{new} is the new candidates DG active powers, p_g^{best} is the best DG active powers during the iteration, and up_p is the maximum value of DG locations and active powers.

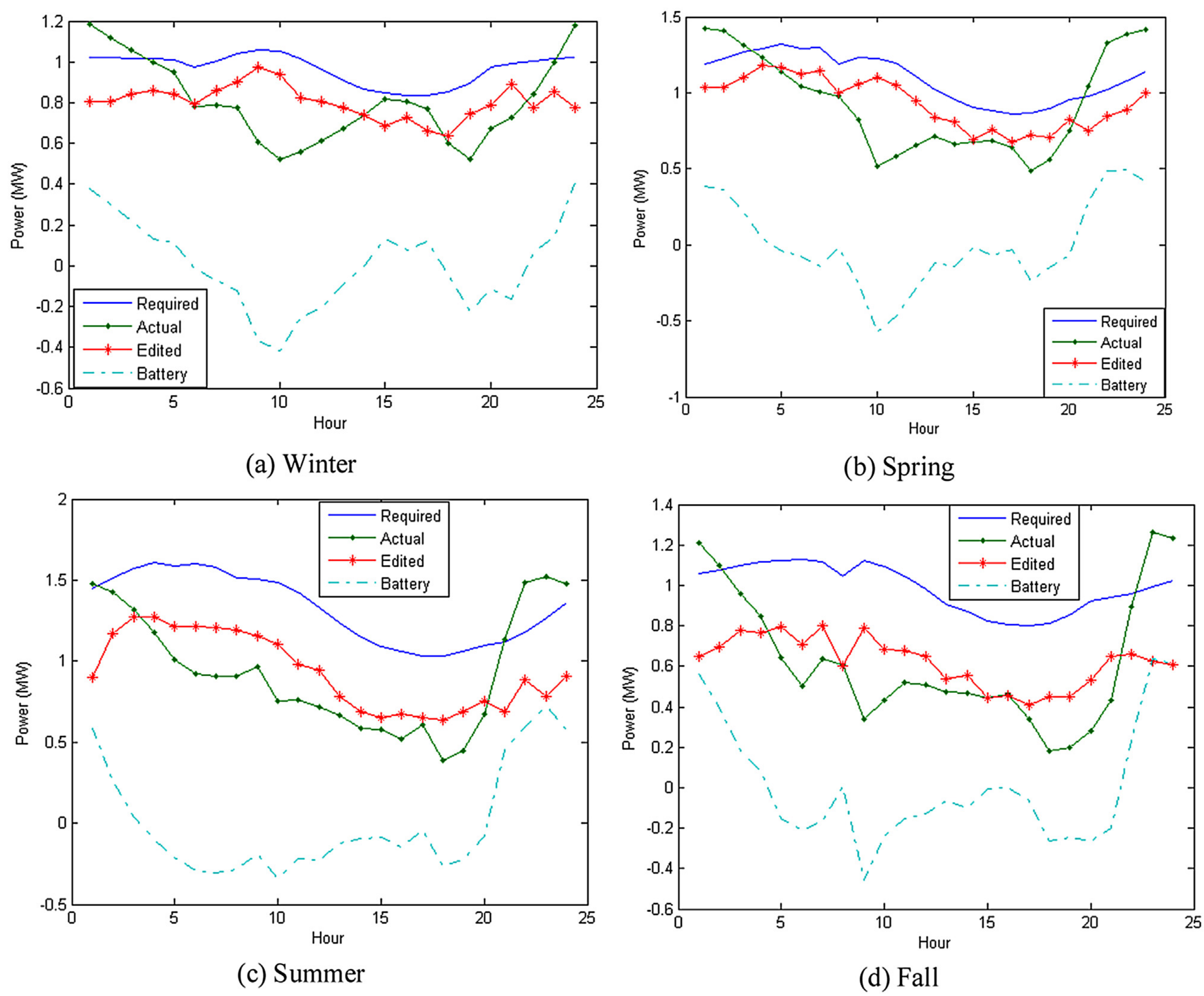


Fig. 7. Optimal power schedule of ESE with wind DG for energy minimization, wind.

6) Repeat Steps (4) and (5) until the convergence criteria is met, the convergence is considered achieved when more than 50% of the DGs' powers are converged to a certain value.
7) Repeat Steps (2)–(6) for all hours until reach the last hour (i.e. h = 96) to obtain optimal power schedule for the DGs.

4.4. Optimal ESEs schedules for energy minimization

This section aims to determine the optimal operation schedule of ESEs connected at same bus with the RES in order to redistribute the actual power schedule of the renewable based DGs (power obtained from the modeling algorithm presented in Ref. [25]) to minimize the differences between the actual power schedule of renewable DGs and the required power schedule (obtained from part C) that minimizes the energy purchased. The proposed algorithm is described by the following procedure.

1) Start with a certain season.
2) Generate "*N*" sets each of 24 random values of different signs. The sum of the 24 values in each set must equals to zero (each of these sets represents a possible operation schedule of ESE).
3) Add each of these sets to the actual power schedule of the renewable DG at the current season to generate "*N*" edited power schedule (edited power schedule is the power schedule of the RES in addition to the ESE power).
4) Calculate the root mean square error (RMSE) between the edited power schedules and the required power schedule using Eq. (15).

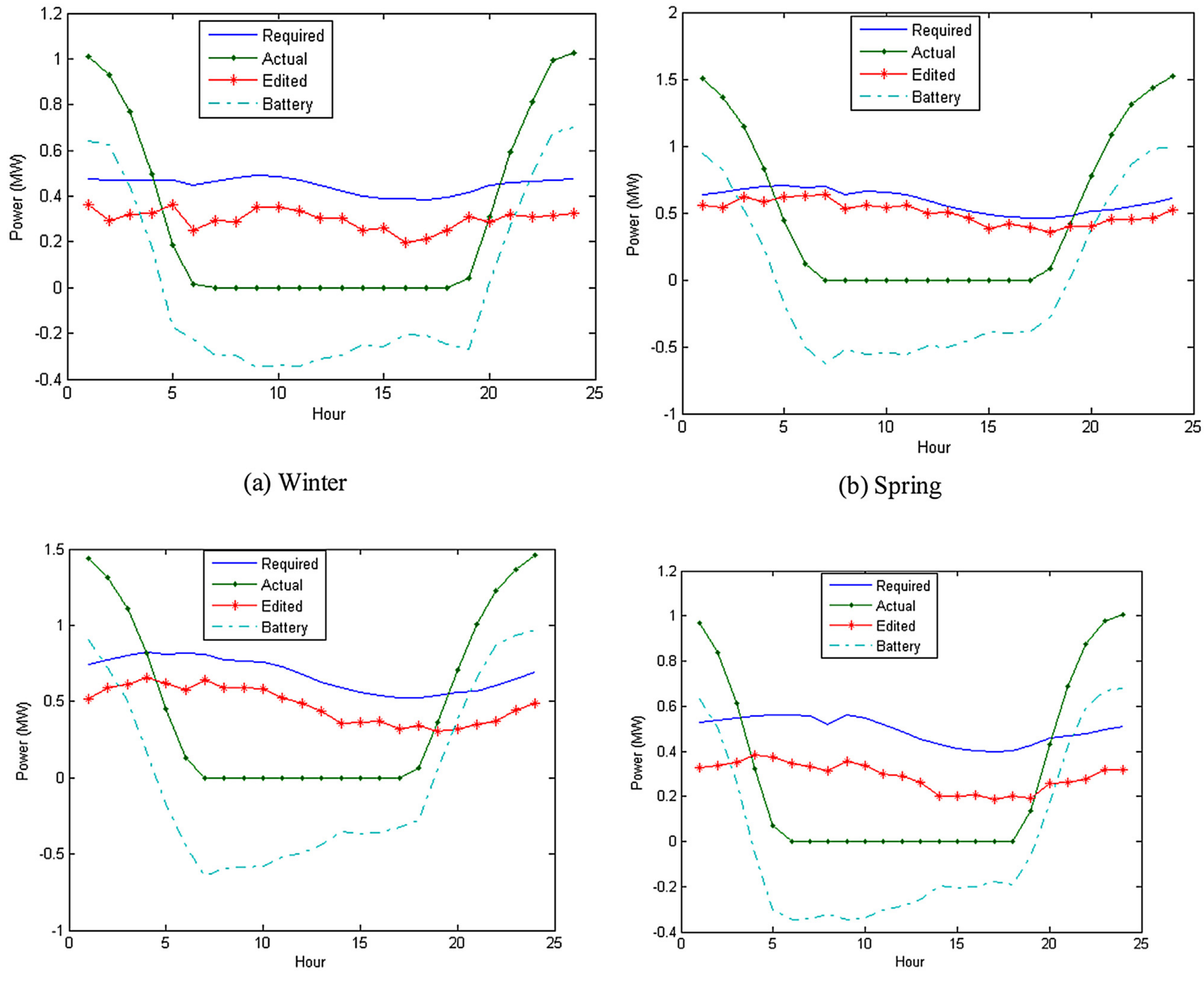
$$RMSE = \sqrt{\sum_{h=1}^{24} (P^{h}_{edited} - P^{h}_{required})^2} \qquad (15)$$

5) Select the best operation schedule of the ESE among the *N* sets (i.e. the set that achieves minimum RMSE).
6) Update each ESE power in all other sets at each hour using Eq. (16) taking into consideration the ESE operation constraints.

$$|P^{h}_{new}| = |P^{h}_{best}| + \frac{P_{max} \times Randn}{it^2}, \forall h, N \qquad (16)$$

Where: P^{h}_{best} is the output power at hour *h* of the best ESE operation schedule set obtained from Step (5) and P^{h}_{new} is the updated output power at hour *h* of each of the remaining sets.

7) Repeat Steps (3)–(6) until the convergence criterion is met, the convergence is considered achieved when more than 50% of the *N* sets converged to the same values.



(a) Winter (b) Spring

(c) Summer (d) Fall

Fig. 8. Optimal power schedule of ESE with wind DG for energy minimization, PV.

8) Repeat for other seasons.

5. Test cases and results

The VPP used in both studies consists of the following components:

- Wind based DG of rated capacity of 2.1 MW.
- PV based DG of rated capacity of 2.12 MW.
- Controllable loads.
- Two energy storage elements each connected at a DG bus.

5.1. Model of renewable energy DGs and system demand

The converged Monte Carlo simulations of the 96 h of the four seasons (typical day model) are obtained for two wind turbines of the characteristics presented in Table 1 and 40,000 PV modules of the characteristics presented in Table 2 and for the system demand. The converged MC results of the aggregated power of the two wind turbines are displayed in Fig. 1 and the total converged output power of the 40,000 PV modules is presented in Fig. 2 and the load profile is shown in Fig. 3.

5.2. Results of the optimal allocation of the RES for energy minimization

The proposed optimization algorithms are implemented in MATLAB and tested on the IEEE 37 nodes unbalanced feeder presented in Fig. 4 to determine the optimal location of wind based DG of power schedule and PV based DG of power schedule. The optimal locations of the RES and the corresponding annual energy are presented in Table 3.

5.3. Results of optimal load control

The methodology described in Section 4.2 is applied to the IEEE 37 nodes feeder to obtain the optimal load control schedule while the RES are connected to their optimal locations. The list of controllable loads is presented in Table 4. The optimal load control schedule consisting of the loads to be controlled arranged based on their importance and the corresponding control hour for the four seasons is presented in Table 5. It is obvious that, the optimal hours for control are the hours of high LSF as the load control during these hours' results in significant reduction in the energy purchased from the substation. The reductions in energy purchased due to load control are presented in Table 6.

5.4. Results of DGs optimal power schedule

The methodology described in Section 4.3 is applied to the IEEE 37 nodes feeder is used to obtain the optimal power schedule for the RES, considering them dispatchable, in order to minimize the annual energy purchased from substation. Figs. 5 and 6 depict the optimal required power schedules and actual power schedule for both wind based DG and PV based DG connected to nodes 25 and 7 respectively for each of the four seasons. It could be noted that, it is impossible to achieve the optimal required power schedule as the energy required to achieve it is higher than the actual RES energy. Thus, instead of reaching the optimal power schedule it is required to reach near optimal power schedule using proper ESE operation as discussed in the following section.

5.5. Results of optimal ESEs schedules

The procedure previously explained in Section 4.4 is used to determine the optimal schedule of ESEs connected with the RES in order to minimize the differences between actual and required power schedules.

The edited power schedule and the ESE optimal schedule for the four seasons for the wind DG are presented in Fig. 7 and for the PV DG are presented in Fig. 8. Table 7 presents the annual energy purchased from substation after applying the VPP concept. The Results show a high reduction in the purchased energy from the substation as compared to the base case and the case where RES are only connected without load control or ESEs. Thus, the VPP concept manages the electrical energy in the distribution networks and can be used to minimize the purchased energy from substation.

6. Conclusions

A novel comprehensive study for achieving the optimal operation of the virtual power plant is presented in this paper. Several optimization algorithms based on modification of BB–BC optimization method are proposed. The proposed algorithms aims to determine RES optimal location, optimal load control strategy and optimal operation schedule of energy storage elements for the sake of minimizing the annual energy purchased from substation. The results show a high reduction in the purchased energy from the substation as compared to the base case and the case where RES are only connected without load control or ESEs which emphasizes the importance of using VPP concept in managing the electrical energy.

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