Journal of Applied Sciences

ISSN 1812-5654

OPEN ACCESS Journal of Applied Sciences

ISSN 1812-5654
DOI: 10.3923/jas.2016.189.200

Research Article

An Interior Point Optimization Method for Stochastic Security-constrained Unit Commitment in the Presence of Plug-in Electric Vehicles

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Abstract

Background and Objective: By increasing the penetration level of renewable energies on the generation side and the emergence of new variable load on the demand side, stochastic analysis of the conventional security constrained unit commitment problem has become more important for the secure optimal operation of the electricity market. Today, the increasing utilization of plug-in electric vehicles, which consume electricity rather than fossil fuel for driving, offers new opportunities and challenges to the operation of electric power system. By appropriate managing and day-ahead scheduling of these types of vehicles, challenges can be replaced by opportunities for the power system operation and planning. **Methodology:** In this study, a new method is proposed for stochastic security-constrained unit commitment problem in the presence of wind power generations and plug-in electric vehicles. The method enjoys the advantages of conventional scenario-based approaches and mitigates their barriers by using interior point optimization techniques. The proposed algorithm is implemented on two standard networks: A 6-bus test system and a large-scale 118-bus system. **Results:** This study demonstrate the accuracy and efficiency of the proposed method, especially in large-scale power systems with different types of uncertainties. **Conclusion:** By increasing the speed of simulation, more uncertainties can be modeled and therefore, more realistic and accurate results can be obtained.

Key words: Benders decomposition, electricity market, mixed-integer non-linear programming, power system uncertainties

Received: February 15, 2016 Accepted: March 09, 2016 Published: April 15, 2016

Citation: Mahdi Mehrtash, Masoud Jokar Kouhanjani, Amir Pourjafar and Seyedbehnam Beladi, 2016. An interior point optimization method for stochastic security-constrained unit commitment in the presence of plug-in electric vehicles. J. Applied Sci., 16: 189-200.

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Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Independent System Operators (ISO) accomplish Security-Constrained Unit Commitment (SCUC) in order to design economic and secure generation schedules for the daily electricity market. They apply the comprehensive market information provided by participants, like performance of generating units, generation offer and demand order, capability of transmission lines and so on[1]. The SCUC provides an economically workable unit commitment which is practically acceptable. The corresponding market participants are provided by SCUC-based generation dispatch. Commonly, a satisfactory SCUC solution could be achieved as long as daily market is proper and robust[1].

A large volume of literature is devoted to SCUS solving methods. In Wang *et al.*[2] and Fu *et al.*[3], Augmented Lagrangian Relaxation (ALR) method and an algorithm according to Bender's Decomposition (BD) technique have been proposed, respectively. Constraint reduction and computation speed increase were investigated[4]. Non-convex SCUC and a new method based on quadratic programming were proposed[5]. Effectiveness of two algorithms extensively applied in SCUC, i.e., Mixed-Integer Programing (MIP) and Lagrangian Relaxation (LR), were evaluated[6].

In recent years, uncertainties of the components of power systems have increased drastically. Two most important sources of power system uncertainties are wind generations and price-based loads. Wind energy usage has grown increasingly in power systems in recent years. However, inherent probabilistic and non-dispatchable characteristics of wind energy could lead to problem in power system features such as frequency, voltage and generation sufficiency. In addition, price-based load is considered another uncertain parameter in power system operation and planning. Therefore, regarding Stochastic SCUC as a tool for optimizing power system operation is completely inevitable[7].

Stochastic SCUC problem which is closer to the real performance of large power systems than deterministic SCUC has attracted great interest of researchers. Distribution generations widely utilized in power systems were taken into consideration for SCUC[8]. Scenario-based methods are widely applied to solve SCUC with uncertainties; however, they result in escalating the computational burden. In Mehrtash *et al.*[9], stochastic SCUC was solved according to point estimation method and BD, including significant reduction in the No. of scenarios and calculation time.

Plug-in Electric Vehicles (PEVs) are considered hourly spread and mobile demand in power systems. The accumulated storage ability of PEVs could alter hourly generation portfolio and decrease the performance costs of the grid[10].

Due to the importance of PEV concept and application, a large number of recent studies have concentrated on their related subjects. In Tomic and Kempton[11], the economic capability of PEVs for contributing to regulation services was evaluated. The integration of PEV in power systems was considered[12] and their electricity market problem was investigated[13].

Similar to wind generation, PEV is an uncertain source for grid. Therefore, its random behavior is investigated in different power system problems, especially Stochastic SCUC. The PEVs random behavior in conjunction with stochastic characteristic of wind energy was evaluated in stochastic SCUC[14]. A cooperation model and constraints of PEVs and wind generation in the presence of battery storage were proposed[15]. In the last reference, the model included the distribution pattern of user trips and evaluated the dynamic process of stored energy. In Krad and Gao[16], the capability of PEVs in providing contingency reserves was investigated. Power system operation and control from the aspect of being influenced by contributing battery-based energy storage transportation by railway transportation network was studied[17].

New Interior Point Optimization Techniques (IPOPT) are capable to solve large-scale Mixed-Integer Non-Linear Programing (MINLP) problems[18]. In this study, a new method is proposed for Stochastic SCUC problem in the presence of wind power generations and PEVs. This method enjoys the advantages of conventional scenario-based approaches and mitigates their barriers using IPOPT techniques. Instead of linearizing, in the proposed method, non-linear problem is solved via IPOPT techniques. Moreover, since the number of Benders's cuts is reduced, the number of master problem solving iterations in BD is lessened and the simulation time is decreased considerably.

The rest of this study is organized as follows: Interior point method is presented in Section 2. Problem formulation and solution methodology are presented in Sections 3 and 4, respectively. The result of the case studies is given in Section 5. Finally, the conclusion is presented in Section 6.

MATERIALS AND METHODS

Interior point method: Advantages of IPOPT for solving large-scale problems will be more understandable when it is compared with Simplex method. Simplex, introduced by

Dantzig[19], is a method for solving Linear Programing (LP). Algorithms based on Simplex method search vertices of the feasible region; therefore, for large-scale problems, in which the number of vertices is high, the solution time is considerable. As a result, Simplex is categorized among exponential time algorithms. In other words, time needed by Simplex for solving an LP problem is an exponential function of the problem scale[20].

Interior point approach was proposed by Karmarkar[21]. Its algorithm's search path is inside the feasible region; in fact, central points should be investigated (Fig. 1). Thus, the problem scale is not too critical and it can be considered among polynomial time algorithms[20]. A complete comparison between Simplex and IPOPT was proposed[22].

At first, interior point approach was proposed only for LP problems. However, the idea of using this method for Non-Linear Programing (NLP) became popular immediately. Recently, COUENNE, which is a new algorithm based on IPOPT, has been proposed by Belotti *et al.*[23]. The COUENNE is an open-source solver for non-convex MINLPs[18]. In order to overcome MINLP challenges, COUENNE uses disjunctive cuts and a tight branch-and-bound approach[24]. This solver was implemented in General Algebraic Modeling System (GAMS) as a non-commercial solver. In this study, GAMS/COUENNE is used to solve Stochastic SCUC as an MINLP problem.

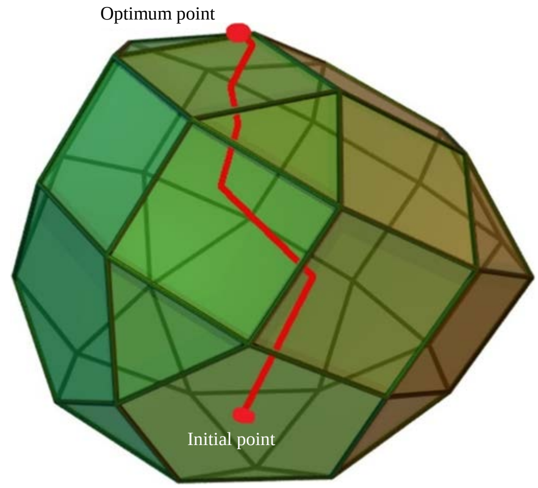

Fig. 1: Search path of IPOPT method

$$\text{Min}[\sum_t\sum_i(p^b.F_{c,i}(P_{i,t})+SU_{i,t}+SD_{i,t})+\sum_t\sum_k p^b.(SU_{k,t}+SD_{k,t})+\sum_t\sum_v p^b.C_{v,t}]$$
$$+[\sum_t\sum_i(F^r_{c,i}(\Delta^{max}_{i,t}))]+\sum_s p^s.[\sum_t\sum_i F_{c,i}(P^s_{i,t})+\sum_t\sum_k(SU^s_{k,t}+SD^s_{k,t})+\sum_t\sum_v C^s_{v,t}] \quad (1)$$

Stochastic SCUC problem formulation: Concepts of corrective and preventive actions and definition of Stochastic SCUC problem have been mentioned in author's previous study[9]. In this section, only the formulation of the problem is discussed.

Objective function: Objective function, Eq. 1 consists of generation cost, startup and shutdown costs of thermal and hydro units, operation cost of PEV fleets, availability cost for providing spinning reserve in scenarios and expected cost of corrective actions in scenarios for mitigating uncertainties.

Availability cost is the payment to generators that provides reserves as a corrective action in response to uncertainties. The providing reserve of generators is limited by their ramp up/down capability[25]. The availability cost is considered one-third of the marginal cost of a generator. Thermal units are formulated as non-quick start units; therefore, their scenario commitment status is similar to the base case. Thus, the startup/shutdown costs should not be introduced in the scenarios[14].

Constraints for the base case: In this stage, the values related to the wind, load, PEV, etc. are fixed to their forecasted values. Thus, these formulas are deterministic.

The system power balance constraint is presented in Eq. 2. A detailed formulation of thermal and hydro units constraints is available[25,26]. The base case PEV fleet constraints are mentioned in Eq. 3-10. The net hourly absorbed/delivered energy from/to grid by PEV battery is given in Eq. 3. The charging efficiency, η_v, is defined as the ratio of the energy stored in the PEV battery to the energy drawn from the grid. Equation 4 represents the hourly charge/discharge/idle status of fleets. Obviously, these status are mutually exclusive. Charge/discharge power limitations are given in Eq. 5 and 6. Equation 7 represents the hourly energy balance in PEV batteries. Parameter $N_{v,t}$ denotes connectivity status of PEV fleet to the grid. When PEV fleet is connected to the grid, $N_{v,t} = 1$, it is in the either charge or discharge or idle mode. Once PEV fleet is decoupled from the grid, $N_{v,t} = 0$, the charge/discharge power will be zero according to Eq. 4-6[14]. The capacity limitation of the PEV batteries is mentioned in Eq. 8 and 9. The cost function of the PEV batteries, which is considered as a non-linear function, is given in Eq. 10. The cost function parameters depend on the depth of discharge and cycles to failure of the battery. A complete discussion about PEV battery technologies can be find[27]. Network constraint based on DC power flow is shown in Eq. 11 and 12:

$$\sum_i P_{i,t} + \sum_w P_{w,t} + \sum_v P_{v,t} + \sum_k P_{k,t} = \sum_d P^d_{D,t} \quad (2)$$

$$\begin{aligned} E^{net}_{v,t} &= P_{dc,v,t} - \eta_v.P_{c,v,t} \\ P_{v,t} &= P_{dc,v,t} - P_{c,v,t} \end{aligned} \quad (3)$$

$$I_{dc,v,t} + I_{c,v,t} + I_{i,v,t} = N_{v,t} \quad (4)$$

$$I_{c,v,t}.P^{min}_{c,v} \le P_{c,v,t} \le I_{c,v,t}.P^{max}_{c,v} \quad (5)$$

$$I_{dc,v,t}.P^{min}_{dc,v} \le P_{dc,v,t} \le I_{dc,v,t}.P^{max}_{dc,v} \quad (6)$$

$$E_{v,t} = E_{v,t\text{-}1} - E^{net}_{v,t} - (1 - N_{v,t}).DR_{v,t} \quad (7)$$

$$E^{min}_v \le E_{v,t} \le E^{max}_v \quad (8)$$

$$E_{v,0} = E_{v,NT} \quad (9)$$

$$C_{v,t} = a.\left(P_{v,t}\right)^2 + b.\left(P_{v,t}\right) + c \quad (10)$$

$$PL_{l,t} = \frac{(\theta_{j,t} - \theta_{o,t})}{X_{j,o}} \quad (11)$$

$$\left|PL_{l,t}\right| \le PL^{max}_l \quad (12)$$

Constraints for each scenario: At this stage, which is the stochastic part of the formulation, the values related to wind, load, PEV, etc. are derived from Monte Carlo scenarios. The initial scenarios are generated and then reduced to final scenarios via scenario reduction techniques. Afterwards, the final scenarios are used in the following formulation.

The system's power balance constraint for each scenario is given in Eq. 13. Scenario constraint related to the thermal and hydro units is mentioned[28]. The PEV scenario constraint is formulated in Eq. 14-21. The equations are similar to those described in the base case section, with the only difference that the deterministic forecasted values for wind, load, PEV, etc. are replaced by their value obtained from the final Monte Carlo scenarios. Parameter NE^s_v, one of the uncertain inputs, denotes ratio of the number of PEVs in scenarios to the number of base case PEVs. The corrective action for the scenarios is enforced by Eq. 22, while the hourly cost of corrective action, $F^r_{c,i}(\Delta^{max}_{i,t})$, is included in the objective function[14]. Equation 22 shows the correlation between generation of a unit in the base case, $P_{i,t}$ and its generation in scenarios, $P^s_{i,t}$. Network constraint based on DC power flow for each scenario is presented in Eq. 23 and 24:

$$\sum_i P^s_{i,t} + \sum_w P^s_{w,t} + \sum_v P^s_{v,t} + \sum_k P^s_{k,t} = \sum_d P^{d,s}_{D,t} \quad (13)$$

$$\begin{aligned} E^{net,s}_{v,t} &= P^s_{dc,v,t} - \eta_v.P^s_{c,v,t} \\ P^s_{v,t} &= P^s_{dc,v,t} - P^s_{c,v,t} \end{aligned} \quad (14)$$

$$I^s_{dc,v,t} + I^s_{c,v,t} + I^s_{i,v,t} = N_{v,t} \quad (15)$$

$$I^s_{dc,v,t} P^{min}_{c,v}.NE^s_v \le P^s_{c,v,t} \le I^s_{c,v,t} P^{max}_{c,v} NE^s_v \quad (16)$$

$$I^s_{dc,v,t} P^{min}_{dc,v} NE^s_v \le P^s_{dc,v,t} \le I^s_{dc,v,t} P^{max}_{dc,v}.NE^s_v \quad (17)$$

$$E^s_{v,t} = E^s_{v,t-1} - E^{net,s}_{v,t} - (1 - N_{v,t}).DR^s_{v,t}.NE^s_v \quad (18)$$

$$E^{min}_v.NE^s_v \le E^s_{v,t} \le E^{max}_v.NE^s_v \quad (19)$$

$$E^s_{v,0} = E^s_{v,NT} = E_{v,0}.NE^s_v \quad (20)$$

$$C^s_{v,t} = a.\left(P^s_{v,t}\right)^2 + b.\left(P^s_{v,t}\right) + c \quad (21)$$

$$\begin{aligned} -\Delta^{max}_{i,t} &\le P^s_{i,t} - P_{i,t} \le \Delta^{max}_{i,t} \\ P^{min}_i.I_{i,t} &\le P^s_{i,t} \le P^{max}_i.I_{i,t} \end{aligned} \quad (22)$$

$$PL^s_{l,t} = \frac{\theta^s_{j,t} - \theta^s_{o,t}}{X_{jo}} \quad (23)$$

$$\left|PL^s_{l,t}\right| \le PL^{max}_l \quad (24)$$

Solution methodology: The scenario-based Stochastic SCUC problem in the presence of PEVs, modeled in Eq. 1-24, is a non-linear, non-convex, large-scale and polynomial-time

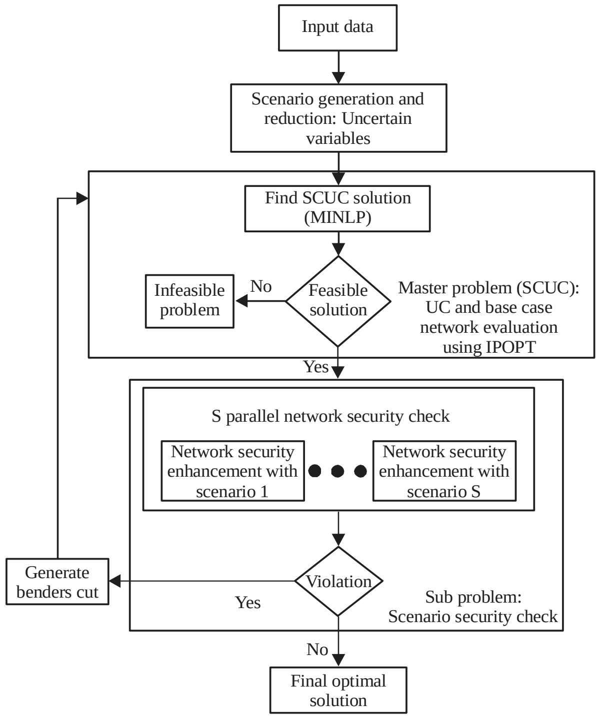

Fig. 2: Flowchart of the proposed method

hard (NP-hard) problem. Solving such a problem for large-scale power systems would be intractable without decomposition[9].

The flowchart of the proposed method is shown in Fig. 2. According to the flowchart, Stochastic SCUC problem is solved at three stages.

At the first stage, Monte Carlo scenarios are generated and reduced to the final scenarios. Due to the high simulation time of Stochastic SCUC problem, scenario reduction must be done before solving the main problem[26].

Afterwards, BD is used for solving the problem[14]. Although, some new IPOPT solvers, such as COUENNE, are able to solve this problem without BD, it can be concluded from the simulation of the sample case studies that the simulation time decreases significantly using BD.

At the second stage, a deterministic SCUC problem, master problem, is solved using IPOPT.

At the third stage, the results of the master problem should be evaluated in the scenario security check subproblem for each final scenario. Every violation will be referred to the master problem, second stage, for adding new constraints based on the generated Bender's cuts. Finally, all the constraints are met in all final scenarios.

This algorithm has two main improvement compared to the previous algorithms proposed for Stochastic SCUC problem[14]. First, the master problem is solved as an MINLP by IPOPT, instead of a, MIP, by Simplex based methods. As mentioned in Section 2, interior point solvers, such as COUENNE, include better features to handle large-scale problems. The ability of these solvers for solving MINLPs is illustrated in the next section by a case study simulation. Second, due to the ability of the IPOPT solvers, UC and network evaluation check are solved at a single stage. However, in previous algorithms, UC is solved at stage one and the network evaluation check is solved as a BD subproblem at stage two. Combination of the UC and network evaluation check at a single stage can improve the simulation time, due to a considerable amount of the total simulation time belongs to master problem. Reducing the subproblem stages leads to fewer benders' cuts; therefore, fewer iterations of master problem solving are needed. This improvement can be concluded from the simulation results of the case studies in the next section.

RESULTS AND DISCUSSION

In this section, two case studies, a 6-bus test system and a 118-bus power system, are studied to demonstrate the validity of the proposed method for Stochastic SCUC problem in the presence of PEVs. The proficiency of the proposed algorithm with IPOPT is illustrated in comparison to the conventional Simplex-based methods.

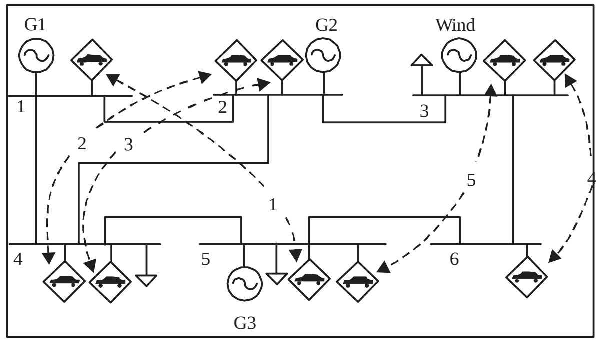

Fig. 3: One-line diagram of 6-bus test system

Table 1: Thermal unit characteristic

Unit	a ($/MW^2)	b ($/MW)	c ($/h)	P_{min} (MW)	P_{max} (MW)	SU ($)	SD ($)	Min.Up (h)	MinDn. (h)
G1	0.099	6.589	211.4	100	320	100	50	4	3
G2	0.203	7.629	217.4	10	160	200	40	3	2
G3	0.494	10.070	102.8	10	100	80	10	1	1

Table 2: Transmission line characteristics

Line ID	From bus	To bus	Impedance (P.U.)	Capacity (MW)
1	1	2	0.170	65
2	1	4	0.258	80
3	2	4	0.197	64
4	5	6	0.140	77
5	3	6	0.018	75
6	2	3	0.037	80
7	4	5	0.037	65

Table 3: Hourly forecasted load and wind power for 6-bus system

Hours	P_{load} (MW)	P_{wind} (MW)
1	197.27	44
2	211.81	70.2
3	211.20	76
4	213.05	82
5	215.15	84
6	220.03	84
7	246.05	100
8	261.36	100
9	255.20	78
10	253.08	64
11	295.75	100
12	295.29	92
13	293.56	84
14	291.24	80
15	294.17	78
16	259.01	32
17	234.00	4
18	222.06	8
19	230.37	10
20	213.61	5
21	218.97	6
22	254.82	56
23	254.74	82
24	223.87	52

6-bus system: First, the proposed method is implemented on the 6-bus test system shown in Fig. 3. The system includes three thermal generators, one wind farm, seven transmission lines, three load points and five PEV fleets. The loads located on buses 3, 4 and 5 consume 20, 40 and 40% of the total load, respectively.

The parameters of the thermal units and transmission lines are shown in Table 1 and 2, respectively. Table 3 shows the hourly forecasted load and wind power generation of the system. In order to show the capability of the proposed method at high volatility of power generation, the penetration level of the wind power (ratio of the wind power generation to the total generation) is increased to 40% at some hours. As a result, a large amount of generation is probabilistic at those hours. The hourly penetration level of the wind power is given in Fig. 4.

The PEV fleet characteristics and their travel pattern are presented in Table 4 and 5, respectively. Charging efficiency of each fleet, which is the ratio of energy stored in the battery to the energy drawn from the grid, is assumed 85%[14]. The annular driving distance by a PEV fleet is 12000 mile and its average per day is 32.88 mile[29,30]. The energy required by a single PEV is about 9 kWh/day with the average 3.65 mile/kWh[11]. Therefore, the hourly energy required by fleet one to five is 7.65, 9.00, 2.25, 7.20 and 4.50 MWh, respectively[14].

Four cases are studied on the 6-bus test system:

- Deterministic SCUC with Simplex (conventional method)
- Deterministic SCUC with IPOPT (proposed method)
- Stochastic SCUC with Simplex (conventional method)
- Stochastic SCUC with IPOPT (proposed method)

Case 1: In this case, the uncertainties are modeled with their forecasted values. Due to the ignorance of the uncertainties,

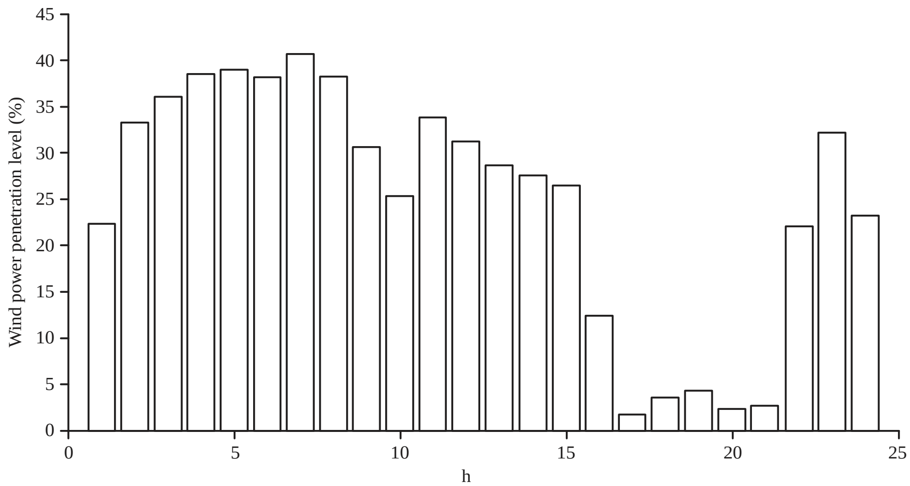

Fig. 4: Penetration level of wind power in 6-bus test system

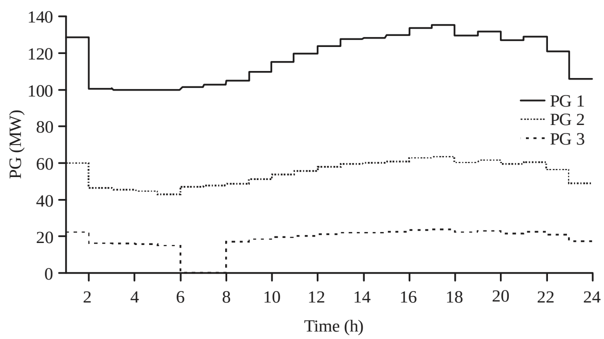

Fig. 5: Generation scheduling of thermal units in case 1

Table 4: PEV fleet characteristics for 6-bus system

PEV fleet No.	Min cap. (MWh)	Max cap. (MWh)	Min charge/Discharge (MW)	Max charge/Discharge (MW)	a ($/MW^2)	b ($/MW)	c ($/h)
1	13.152	65.76	7.3/6.2	24.8/21.08	0.17	8.21	0
2	10.96	54.8	7.3/6.2	14.58/12.4	0.20	8.21	0
3	5.48	27.4	7.3/6.2	7.29/6.2	0.41	8.21	0
4	8.768	43.84	7.3/6.2	11.67/9.92	0.25	8.21	0
5	10.96	54.8	7.3/6.2	14.58/12.4	0.20	8.21	0

Table 5: PEV fleet travel characteristics for 6-bus system

		1st trip departure		1st trip arrival		2nd trip departure		2nd trip arrival	
PEV fleet No.	No. of PEVs	Time	Bus	Time	Bus	Time	Bus	Time	Bus
1	3.400	6:00	5	8:00	1	17:00	1	19:00	5
2	2.000	7:00	4	8:00	2	16:00	2	17:00	4
3	1.000	5:00	4	7:00	2	16:00	2	18:00	4
4	1.600	5:00	6	6:00	3	17:00	3	18:00	6
5	2.000	7:00	5	9:00	3	18:00	3	20:00	5

there is no need to generate either Monte Carlo scenarios or scenario security check subproblem. The deterministic SCUC problem is solved as an MIP problem using CPLEX solver of GAMS[18]. Quadratic cost functions are linearized in order to solve the problem using a Simplex solver, i.e., CPLEX. The BD is used to decompose the problem into a master UC problem and a network security check subproblem as explained[14]. The operation cost is 97091.741 $. Generation scheduling of thermal units and power dispatch of PEVs is demonstrated in Fig. 5 and Table 6, respectively.

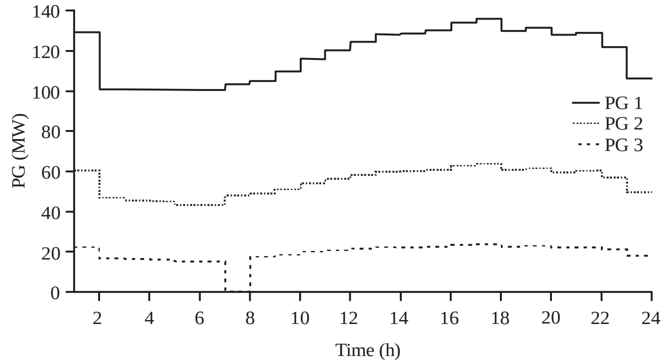

Fig. 6: Generation scheduling of thermal units in case 2

Table 6: Power dispatch of PEVs in case 1

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
-15.47	-6.63	-7.78	-8.63	-10.77	0	0	-4.07	-1.30	0	0	0	0	0	0	2.06	0	0	0.67	0	0	0	0	0
-12.89	-4.56	-5.52	-6.25	-8.05	-4.22	0	-2.38	-0.07	0	0	0	0	0.32	1.06	0	3.79	0.83	1.82	0	0.57	0	0	0
-6.44	-2.42	-2.90	-3.24	0	0	-1.84	-1.36	-0.21	0	0	0	0	0	0.30	0	0	0.17	0.65	0	0.06	0	0	0
-10.31	-3.85	-4.62	-5.20	0	-3.57	-2.90	-2.11	-0.21	0	0	0	0	0	0.61	2.20	0	0.43	1.22	0	0.23	0	0	0
-12.89	-4.78	-5.74	-6.46	-8.30	-4.43	0	0	-0.26	0	0	0	0	0.06	0.81	2.71	3.56	0	0	0	0.33	0	0	0

Table 7: Power dispatch of PEVs in case 2

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
-15.47	-6.65	-7.86	-8.70	-10.82	0	0	-4.02	-1.26	0	0	0	0	0	0	2.10	0	0	0.74	0	0	0	0	0
-12.89	-4.32	-5.39	-6.10	-7.91	-7.78	0	-2.12	0	0	0	0	0.30	0.57	1.31	0	4.08	1.21	2.14	0.12	0.84	0	0	0
-6.44	-2.43	-2.95	-3.28	0	0	-1.80	-1.35	-0.18	0	0	0	0	0	0.28	0	0	0.19	0.67	0	0.06	0	0	0
-10.31	-3.66	-4.50	-5.07	0	-6.40	-2.63	-1.89	-0.07	0	0	0	0	0.23	0.87	2.42	0	0.70	1.49	0	0.45	0	0	0
-12.89	-4.49	-5.52	-6.25	-8.06	-7.92	0	0	0	0	0	0	0.13	0.39	1.15	3.13	3.91	0	0	0	0.68	0	0	0

Table 8: Probability of final scenarios

Scenario	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Probability	0.053	0.002	0.080	0.001	0.003	0.075	0.003	0.031	0.030	0.003	0.005	0.003	0.089	0.595	0.027

Case 2: In this case, the deterministic SCUC problem is solved as an MINLP problem using COUENNE solver of GAMS[18]. As mentioned in Section 2, due to the capability of this solver, there is no need to either linearize or decompose the problem. The operation cost is 97067.693 $. Power dispatch of PEVs and generation scheduling of thermal units are given in Table 7 and Fig. 6, respectively.

As given in Fig. 5 and 6, using the proposed method, the third thermal unit schedule at h 6 is on, while it is off in case 1. Moreover, the total operation cost is decreased by 24.048 $, which is an improvement in the schedule that leads to less operation cost. This decrease in the operation cost is the result of solving the problem as an MINLP without accepting the errors of linearizing the cost functions.

Case 3: For considering uncertainties, wind power generation, load points and No. of PEVs in fleets are modeled by normal distribution functions. Their mean is set to their forecasted values and their standard deviations are assumed as 10, 5 and 10% of the forecasted values, respectively. Stochastic SCUC problem is solved as an MIP problem using CPLEX solver of GAMS. Quadratic cost functions are linearized in order to solve the problem using Simplex solver, i.e., CPLEX. The BD is used to decompose the problem into a master UC problem and two subproblems, a network security check subproblem and a scenario security check subproblem[14]. To run the Monte Carlo simulation, initially, 10000 random scenarios are generated and then, they are reduced to 15 final scenarios using the fast backward/forward technique of SCENRED library of GAMS software GAMS/SCENRED (http://www.gams.com/). The probability of each final scenario is given in Table 8. The total operation cost is 93311.122 $. Generation scheduling of thermal units and power dispatch of PEVs are shown in Fig. 7 and Table 9, respectively.

Case 4: In this case, Stochastic SCUC problem is solved as an MINLP problem using COUENNE solver of GAMS. As mentioned in Section 2, due to the capability of this solver,

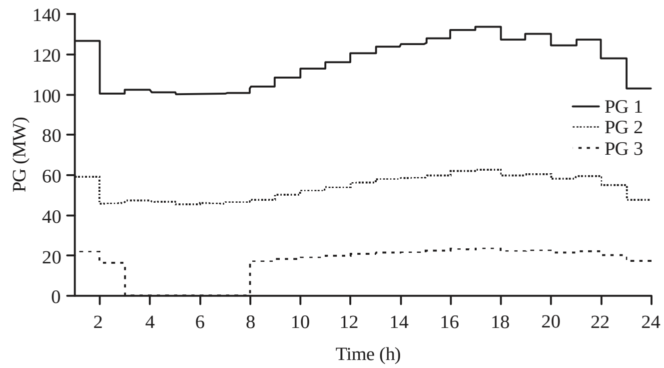

Fig. 7: Generation scheduling of thermal units in case 3

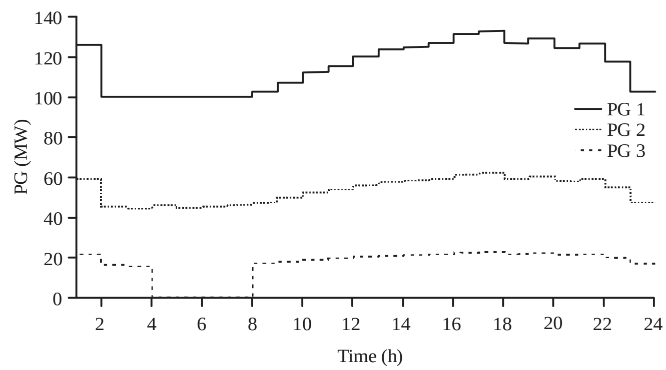

Fig. 8: Generation scheduling of thermal units in case 4

Table 9: Power dispatch of PEVs in case 3

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
-15.47	-7.84	-6.12	-6.77	-8.09	0	0	-5.42	-2.51	0	0	0	0	0	0	0.66	0	0	0	0	0	0	0	0
-12.89	-5.07	-3.6	-4.16	-5.28	-5.04	0	-3.01	-0.54	0	0	0	0	0	0.23	0	3.12	0.13	1.23	0	0	0	0	0
-6.44	-2.62	-1.91	-2.18	0	0	-2.33	-1.62	-0.41	0	0	0	0	0	0	0	0	0	0.42	0	0	0	0	0
-10.31	-4.05	-2.88	-3.33	0	-4.03	-3.57	-2.41	-0.43	0	0	0	0	0	0.18	1.95	0	0.1	0.98	0	0	0	0	0
-12.89	-5.52	-4.06	-4.62	-5.74	-5.5	0	0	-1.01	0	0	0	0	0	0	1.9	2.59	0	0	0	0	0	0	0

Table 10: Power dispatch of PEVs in case 4

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
-15.47	-7.52	-8.8	-6.34	-7.8	0	0	-4.92	-2.06	0	0	0	0	0	0	1.25	0	0	0	0	0	0	0	0
-12.89	-5.04	-6.13	-4.02	-5.28	-4.96	0	-2.83	-0.4	0	0	0	0	0	0.52	0	3.43	0.52	1.6	0	0.3	0	0	0
-6.44	-2.55	-3.09	-2.07	0	0	-2.14	-1.48	-0.29	0	0	0	0	0	0.14	0	0	0.11	0.64	0	0	0	0	0
-10.31	-4.04	-4.91	-3.21	0	-3.96	-3.37	-2.27	-0.33	0	0	0	0	0	0.41	2.11	0	0.39	1.23	0	0.23	0	0	0
-12.89	-5.34	-6.44	-4.35	-5.58	-5.26	0	0	-0.7	0	0	0	0	0	0.17	2.29	3.08	0	0	0	0	0	0	0

Table 11: Total operation cost and simulation time for all cases

Parameters	Case	Solution method	Total operation cost ($)	Total simulation time (sec)
Base case (Deterministic)	1	Simplex	97091.741	100
	2	IPOPT	97067.693	55
Stochastic analysis	3	Simplex	93311.122	2235
	4	IPOPT	93282.094	1810

there is no need to linearize the problem. The problem is solved using BD based on the proposed algorithm as shown in Fig. 2. The operation cost is 93282.094 \$. Power dispatch of PEVs and generation scheduling of thermal units are given in Table 10 and Fig. 8, respectively. The operation cost and simulation time of all the four cases are presented in Table 11.

By comparing Fig. 7 and 8, we understand that, in contrast to case 3, in case 4, the third thermal unit is off at 3 h.

Table 12: Wind farms hourly generation power for 118-bus system

	Wind power (MW)				Wind power (MW)		
Hours	W1(bus 36)	W2 (bus 77)	W3 (bus 69)	Hours	W1(bus 36)	W2 (bus 77)	W3 (bus 69)
1	177.25	210.91	207.02	13	114.18	92.767	107.20
2	171.03	206.65	211.71	14	109.21	93.605	101.49
3	157.58	197.16	210.79	15	106.82	83.711	101.26
4	145.43	189.44	204.20	16	111.48	85.596	106.67
5	142.40	175.42	200.00	17	102.70	85.328	112.46
6	137.77	143.91	198.43	18	90.549	77.945	120.81
7	119.20	111.31	181.72	19	99.545	76.884	122.88
8	109.45	80.783	147.92	20	120.28	91.872	130.31
9	115.52	58.678	120.91	21	126.64	116.290	160.06
10	116.31	60.474	113.06	22	136.70	123.330	181.18
11	116.79	82.159	115.21	23	160.15	116.350	194.02
12	114.89	90.131	113.64	24	175.23	102.620	202.23

Table 13: PEV fleet characteristics for 118-bus system

PEV fleet	Min energy (MWh)	Max energy (MWh)	Charge/Discharge min (kW)	Charge/Discharge max (MW)	a ($/MW^2)	b ($/MW)	c ($/h)
1	131.52	986.4	7.3/6.2	248.0/210.8	0.57	27.35	0
2	109.60	822	7.3/6.2	145.8/124	0.68	27.35	0
3	54.80	411	7.3/6.2	72.9/62	1.36	27.35	0
4	87.68	657.6	7.3/6.2	116.7/99.2	0.85	27.35	0
5	109.60	822	7.3/6.2	145.8/124	0.68	27.35	0

Table 14: Total operation cost and simulation time for all cases of 118-bus system

Parameters	Case	Solution method	Total operation cost ($)	Total simulation time (min)
Base case (Deterministic)	1	Simplex	1,323,900	170
	2	IPOPT	1,323,780	113
Stochastic analysis	3	Simplex	1,300,850	3490
	4	IPOPT	1,299,100	2262

Moreover, the total operation cost is decreased by 29.028 $. Therefore, as shown in Table 11, it can be concluded that solving Stochastic SCUC problem as an MINLP with IPOPT leads to less final operation cost due to the elimination of linearizing errors. Besides, the simulation time decreases due to mitigating the iterations of master UC problem by decreasing the number of the required Benders' cuts.

118-bus system: For scenario-based Stochastic SCUC problem in large-scale power systems, the computational burden is drastically intensified and efficient reduction of CPU time is necessary. Moreover, the advantage of the proposed method in a large-scale power system with numerous uncertainties can be better comprehended.

In the second part of the case studies, the proposed method is implemented on a 118-bus test system, which includes 54 thermal generators, 9 transformers, 186 transmission lines and 91 load points. The system is modified by adding three wind farms and five PEV fleets. The location and the hourly generation of the three wind farms are given in Table 12. Totally, 100000 PEVs are divided into 5 fleets. The number of PEVs in fleet 1 through 5 is 34000, 20000, 10000, 16000 and 20000, respectively[14]. The fleet characteristics are shown in Table 13. The PEVs' travel characteristics are similar to those in the previous case study (Table 5).

Four cases are implemented on this system and the results are given in Table 14. As shown in this table, the proposed method based on IPOPT reduces both operation cost and simulation time for the Stochastic SCUC of such large-scale power systems.

CONCLUSION

In this study, a new method based on interior point optimization has been proposed for scenario-based Stochastic SCUC in the presence of PEVs. Whereas, the proposed method enjoys the advantages of the scenario-based method, it also mitigates the obstacles of this method, e.g., time consuming simulation due to computational burden and linearizing errors. By increasing the speed of simulation, more uncertainties can be modeled and, therefore, more realistic and accurate results can be obtained. The proposed algorithm has been implemented on two standard networks: A 6-bus test system and a large-scale 118-bus system. These case studies demonstrate the accuracy and efficiency of the proposed method especially in the large-scale power systems with different type of uncertainties.

ACKNOWLEDGMENT

This research was supported by Young Researchers and Elite Club, Dariun Branch, Islamic Azad University, Dariun, Fars, Iran. We thank Hamid Dehghanfar, Dean of Young Researchers and Elite Club, for assistance with supporting our study.

APENDIX NOMENCLATURE

Variables		
j, o	=	Index of buses
$C_{(.)}^{(.)}$	=	Operation cost of PEV fleet
$E_{v,t}^{(.)}$	=	Available energy in batteries of PEV fleet v at time t
$E_{v,t}^{net}$	=	Net discharge energy of PEV fleet v at time t
$F_{c,(.)}, F_{c,(.)}^{r}$	=	Production/availability cost function of a thermal unit
i	=	Denotes a thermal unit
$I_{(.)}^{(.)}$	=	Unit statue indicator, 1 means on and 0 means off
$I_{c,(.)}^{(.)}$	=	Indicator of PEV fleet in charging mode
$I_{dc,(.)}^{(.)}$	=	Indicator of PEV fleet in discharging mode
$I_{i,(.)}^{(.)}$	=	Indicator of PEV fleet in idle mode
k	=	Denotes a hydro unit
l	=	Index of transmission line
$P_{(.)}^{(.)}$	=	Generation of a unit
$P_{c,(.)}^{(.)}, P_{dc,(.)}^{(.)}$	=	Charge/discharge power of PEV fleet
$PL_{l,t}^{(.)}$	=	Real power flow on line l at hour t
s	=	Denotes a scenario
$SD_{(.)}^{(.)}$	=	Shutdown cost of a unit
$SU_{(.)}^{(.)}$	=	Startup cost of a unit
t	=	Hour index
v	=	Denotes a PEV fleet
w	=	Denotes a wind unit
$\theta_{(.)}^{(.)}$	=	Bus angle
$\Delta_{(.)}^{max}$	=	Maximum permissible power adjustment of a unit
Constants		
a, b, c	=	Cost function coefficients
$DR_{v,t}^{s}$	=	Energy for PEV v to drive at time t in scenario s
E_{v}^{min}, E_{v}^{max}	=	Min/max energy stored in batteries of PEV fleet v
$E0_{v}, ET_{v}$	=	Initial and terminal stored energy in PEV fleet v
$N_{v,t}$	=	Statue of grid connection of fleet v at time t
NE_{v}^{s}	=	Ratio of the number of PEVs in fleet v in scenario s to the number of base case PEVs
NT	=	No. of hours under study
P^{b}	=	Probability of the base case solution
P^{s}	=	Probability of scenario s
$P_{(.)}^{min}, P_{(.)}^{max}$	=	Min/max generation capacity
$P_{c,v}^{min}, P_{c,v}^{max}$	=	Min/max charging capacity of PEV fleet v
$P_{dc,v}^{min}, P_{dc,v}^{max}$	=	Min/max discharging capacity of PEV fleet v
$P_{D,(.)}^{(.)}$	=	Total system demand
PL_{l}^{max}	=	Maximum capacity of line l
$X_{j,o}$	=	Inductance of a line between buses j and o
η_{v}	=	Cycle charging efficiency of PEV fleet

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