TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.5, May 2014, pp. 3407 ~ 3415
DOI: http://dx.doi.org/10.11591/telkomnika.v12i5.4953

Cost-Emission Scheduling under Uncertainty in a Smart Grid with Wind Power and PHEVs

Zhang Xiaohua*[1,2], Xie Jun[3], Li Zhenkun[4]
[1]School of Information Science & Engineering, Changzhou University, Changzhou 213164, China
[2]Jiangsu Key Laboratory of Power Transmission and Distribution Equipment Technology
[3]Nanjing University of Posts and Telecommunications, Nanjing, 210046
[4]Shanghai University of Electric Power, Shanghai, 200090
Corresponding author, e-mail: zhang_810301@163.com*, eejxie@gmail.com, lzk021@163.com

Abstract

The rapid development of plug-in electric vehicles (PHEVs) and wind power brings new challenges to power system security and economic operation. Traditional deterministic models fail to capture their extra characteristics. In this paper, PHEVs, wind power and thermal units are studied. The scheduling model with PHEVs and wind power is more complex, which minimizes the cost-emission while considering the uncertainty of wind power and load, the smart charging/discharging of PHEVs, the coordination of wind power and PHEVs. The multi-scenario simulation is presented in the random variable discretization. Numbers of representative scenarios is chosen, so that the original objective of the smart grid is within an acceptable level. Then the multi-agent system (MAS) technology is proposed to divided a day is into 24 time intervals, and each time interval is managed by a work agent to produce a solution set for the time interval. The wind power, PHEVs and thermal units are coordinated by the work agent. 24 work agents are managed a coordination agent that would coordinate the solutions of the work agents. Finally, a smart grid of 10 thermal units, a wind farm and PHEVs are used to demonstrate the effective of the proposed model. The results show that the smart grid can use the wind power and PHEVs most effectively, can greatly cut the operation cost and carbon emission. By the tradeoff between the weight factor of cost and emission, the balance of cost and emission can reach.

Keywords: *PHEVs, multi-scenario simulation, MAS, cost-emission dispatching*

1. Introduction

The power and energy industry in term of economic importance and environmental impact is one of the most important sectors in the world, since every aspect of industrial productivity and daily life are dependent on electricity. It represents a major portion of global emission.

With increasing concern over global climate change, policy makers are promoting renewable energy, which is considered as a means of meeting emission reduction targets. So environment friendly modern dispatching is essential. However, power system researchers have addressed only traditional unit commitment (UC) problems to minimize cost in the existing articles. They consider emission in UC problems rarely, though it is an important factor as mentioned above.

A technical report from the National Renewable Energy Laboratory (NREL) has reported significant reductions in CO_2 emissions from PHEVs [1]. Considering cost advantages, PHEVs have a significant potential market [2]. Because of its energy saving potential, PHEVs' research and application has become the focus attention of countries. The corresponding researchers have mainly concerned on the interconnection of vehicle energy storage and grids. Ahmed Yousuf Saber considers the UC on CO_2 emissions of V2G (Vehicle to Grid), and analyzes the influence of CO_2 emissions and PHEVs discharge in different situations; electric vehicles (EV) can replace conventional small units for power generation, thereby reducing the operation cost and emission of pollutants. But it is assumed that the charging demand of EV has been provided by the renewable energy, and charging load characteristics of EV is not considered [3]. Several other research efforts of PHEVs in recent years [4-8] examine the

Received October 21, 2013; Revised December 4, 2013; Accepted December 23, 2013

impact of PHEVs on the power system but do not take wind energy into account and do not propose operational methods.

However, PHEVs can't completely solve the emission problem alone; they need electric power, which is one of main source of emission. The NREL examines the long-term interaction between wind energy and PHEVs [9] by assuming increasing penetration of PHEVs compared with the current vehicle fleet for future years. The effective control of V2G charging, the formation of renewable energy and PHEVs effective are complementary [10]. Literature [11] takes the Danish power system as an example, analyzes the charging control for the promotion of wind power to absorb and reduce greenhouse gas emissions. Wang et al. [12] uses a deterministic method to address coordination of wind power and PHEV charging. Lisa [13] investigates consequences of integrating PHEVs in a wind-thermal power system. Four different PHEV integration strategies, with different impacts have been investigated. The study shows that PHEVs can impact the CO_2 emission. Soares [14] analyzes PHEVs as a way to maximize the integration of variable renewable energy in power systems.

Deterministic UC deals with the unit generation schedule in a power system. The purpose of such a schedule is to minimize operation costs and emissions while satisfying prevailing constraints such as load balance, system spinning reserve, et al over a set of time periods. Compared with deterministic UC and dispatch methods, stochastic UC studies have been mostly performed in academia. Literature [15] and [16] develop a stochastic UC model to study the impacts of PHEVs on power system operation and scheduling. The uncertainty is addressed in the proposed model by generating different scenarios.

Traditional UC only can dispatch generator but not load. Load dispatch can play an important role in reducing the operation cost of power system by shaving the peak and filling the valley of load profiles. The success of practical application of PHEVs greatly depends on the maximum utilization of renewable energy in the smart grid so that emission and cost are reduced. In this paper, the PHEVs, wind power and thermal units are studied, the uncertainty smart grid dispatching model is formulated as a stochastic cost-emission reduction model. In the scheduling, the forecasting load and wind power are used, but the actual wind power and load usually differs from the forecasted ones. So the uncertainties of load and wind power are taken into account. The PHEVs charge/discharge control, the coordination of PHEVs and wind power are considered. First, the multi-scenario simulation is used in the random variable discretization. Numbers of representative scenarios is chosen, so that the original objective of the smart grid is within an acceptable level. Then a day is divided into 24 time intervals, and each time interval is managed by a work agent to produce a solution set for the time interval. The work agent is presented to coordinate the wind power, PHEVs and thermal units. The adjustment of weight factors can reach the effective coordination between CO_2 emissions and costs.

2. Stochastic Cost-emission Reduction Model

2.1. Multi-scenario Simulation

In multi-scenario, a large number of discrete probability distributions are formed to simulate the uncertainty of random variables. It generally has two steps to generate scenarios.

The probability distribution of random variable is obtained by Monte Carlo simulation.

In order to minimize the information loss, the probability distribution of the random variable is dispersed by the approximate method.

Due to the stochastic properties of wind power and load, the wind power and the load is very difficult to predict precisely. Under multi-scenario simulation, some representative discrete scenarios are extracted for the optimization in a smart grid with wind generator and PHEVs under uncertainty, as it is hard to consider all continuous states. However, the total number of scenarios grows exponentially with state variable.

For uncertainty, discrete probability distribution sets for load demand (δ_D) and wind resource (δ_w) are given as follows:

$$\delta_D = \{(p_d{}^1, \rho_d^1); (p_d{}^2, \rho_d^2); \cdots (p_d{}^s, \rho_d^s); \cdots (p_d{}^{nd}, \rho_d^{nd})\} \quad (1)$$

(p_d^s, ρ_d^s) is load and the corresponding probability of uncertain load at scenario s ; nd is the set of possible scenarios derived from load.

$$\rho_d^1 + \rho_d^2 + \cdots + \rho_d^{nd} = 1 \tag{2}$$

$$\delta_w = \{(p_{wind}^1, \rho_\omega^1);(p_{wind}^2, \rho_\omega^2);\cdots(p_{wind}^s, \rho_\omega^s);\cdots(p_{wind}^{nw}, \rho_\omega^{nw})\} \tag{3}$$

$(p_{wind}^s, \rho_\omega^s)$ is wind and the corresponding probability of uncertain wind at scenario s ; nw is the set of possible scenarios derived from wind power.

$$\rho_\omega^1 + \rho_\omega^2 + \cdots + \rho_\omega^{nw} = 1 \tag{4}$$

SC is a set of possible scenarios derived from wind power and load.

$$SC = \delta_D \times \delta_w \tag{5}$$

$$\sum_{s \in SC} \rho_d \rho_\omega = 1 \tag{6}$$

$$\rho_s = \rho_d \rho_w \tag{7}$$

δ_D , δ_w are sets of discrete distribution of load, wind power; ρ_d , ρ_ω are the corresponding probability of uncertain load, wind; ρ_s is the corresponding probability of the smart grid system at scenario s . Difference between the scenario model and the original model is a discrete probability distribution adopted. Curves representing the original probability density distribution, rectangular bars represent the scenarios; the rectangular bar height represents probability of corresponding scenario. Because of wind power and load uncertainty, and EV charging/discharging in smart grid control, so the traditional optimization problem is transformed into uncertainty smart grid dispatching. To capture volatility, we assume the wind power and load are subject to the distribution $N(\mu,\sigma^2)$ with their expected value (μ) and their volatility (σ). Five scenarios are considered for the wind power and load uncertainty, the scenario distribution of wind power and load are shown in Figure1 and 2 respectively.

$$\begin{aligned}\delta_w = \{&(p_w \times 100\%, 0.5);(p_d \times 99\%, 0.15);(p_d \times 101\%, 0.15);\\ &(p_d \times 97.5\%, 0.1);(p_d \times 102.5\%, 0.1)\}\end{aligned} \tag{8}$$

$$\begin{aligned}\delta_D = \{&(p_d \times 100\%, 0.6);(p_d \times 98.5\%, 0.15);(p_d \times 102\%, 0.15);\\ &(p_d \times 98\%, 0.05);(p_d \times 103\%, 0.05)\}\end{aligned} \tag{9}$$

p_w , p_d are the predict value of wind power and load.

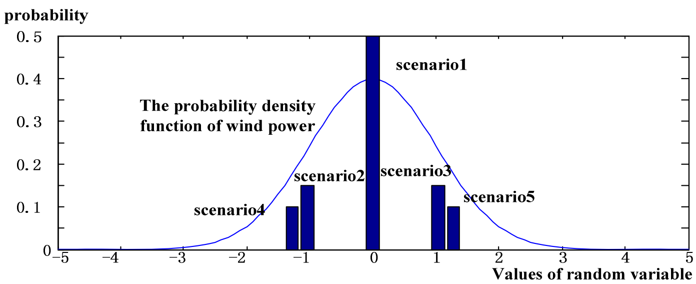

Figure 1. The Scenario Distribution of Wind Power

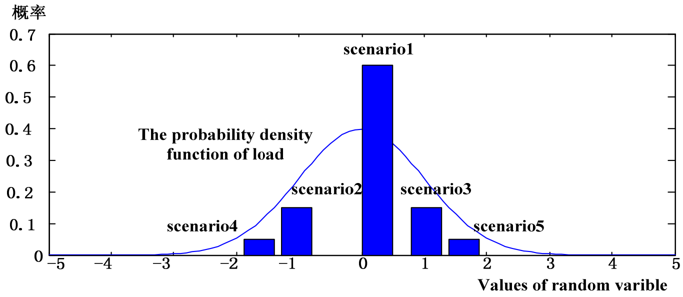

Figure 2. The Scenario Distribution of Load

2.2 Cost-emission Reduction Model under Uncertainties

A quadratic function is considered for the fuel function of thermal units under the deterministic case:

$$FC_i(P_i^t) = a_i + b_i p_i^t + c_i (p_i^t)^2 \tag{10}$$

Considering the uncertainty of load and wind power, the fuel cost function is converted into the scenario model:

$$[FC_i(P_i^t), \rho_s] = [a_i + b_i p_i^{st} + c_i (p_i^{st})^2, \rho_s] \tag{11}$$

p_i^{st} is the power of thermal unit i at time t considering scenario s, ρ_s is the corresponding probability; a_i, b_i, c_i are cost coefficients of unit; i .It is assumed that conventional thermal units are coal-fired. A quadratic function is considered for the emission curve [17] as follows:

$$[E_{ci}(P_i^{st}), \rho_s] = [(\alpha_{ci} + \beta_{ci} p_i^{st} + \gamma_{ci}(p_i^{st})^2) u_i^t, \rho_s] \tag{12}$$

α_{ci} , β_{ci} , γ_{ci} are CO_2 emission coefficients of unit i .Therefore, the objective function for cost-emission optimization considering a set of scenarios s in a smart grid is:

$$\begin{aligned} \min TC^s = \sum_{s \in S} \rho_s \sum_{t=1}^{T} \sum_{i=1}^{N} [& W_c (a_i + b_i p_i^{st} + c_i (p_i^{st})^2) u_i^t + S_i u_i^t (1 - u_i^{t-1}) + \\ & W_e (\alpha_{ci} + \beta_{ci} p_i^{st} + \gamma_{ci}(p_i^{st})^2) u_i^t] \end{aligned} \tag{13}$$

u_i^t is decision variable of unit i at time t, 1 for up, 0 for down; S_i is start-up cost of unit i. N is total numbers of thermal units; T is numbers of periods under study; W_c, W_e is the weight factor of operation cost (fuel cost plus startup cost), CO_2 emission;

$$W_c + W_e = 1 \tag{14}$$

Constraints:
PHEVs are considered as loads or sources. Power supplied from distributed generations must satisfy the load demand:
PHEVs discharging

$$\sum_{i=1}^{N} p_i^t u_i^t + p_v N^t_{v2G} = p_d^t \quad t = 1, 2, \cdots, T \tag{15}$$

PHEVs charging

$$\sum_{i=1}^{N} p_i^t u_i^t = p_d{}^t + p_v N^t{}_{v2G} \quad t = 1,2,\cdots,T \tag{16}$$

All registered PHEVs take part in smart grid operations during a scheduling period,

$$\sum_{t=1}^{T} N_{v2G}^t = N_{v2G}^{\max} \qquad t = 1,2,\cdots,T \tag{17}$$

$N_{v2G}^{\max}$ is the total registered PHEVs; N_{v2G}^t is number of vehicles connected to the grid at hour t To maintain system reliability, adequate spinning reserves are required:
PHEVs discharging

$$\sum_{i=1}^{N} u_i^t p_{i\max} + p_v^{max} N_{v2G}^t \geq p_d^t + R^t \quad t = 1,2,\cdots,T \tag{18}$$

PHEVs charging

$$\sum_{i=1}^{N} u_i^t p_{i\max} \geq p_d^t + p_v^{max} N_{v2G}^t + R^t \quad t = 1,2,\cdots,T \tag{19}$$

$p_{i\max}$ is the maximum output limit of unit; i, p_v^{max} is the capacity of PHEVs; $p_d{}^t$ is system demand at time t; R^t is system spinning reserve requirement at time t; $p_{i\max} / p_{i\min}$ is maximum/ minimum generation level of unit i ;·Number of charging/discharging PHEVs limit.

$$N_{v2G}^t \leq N_{v2G}^{\max t} \qquad t = 1,2,\cdots,T \tag{20}$$

All the PHEVs cannot charge/discharge at the same time. For reliable operation and control, limited number of vehicles will charge/discharge at a time. $N_{v2G}^{\max t}$ is the maximum number of charging/discharging at hour t.

Generation limits, ramp rate, minimum up and down time constraints are also considered.

3. Proposed Solution Approach

The total scheduling period is 24h, and it contains 24 work agents in the scheduling period. Each work agent uses genetic algorithm to produce a solution set for the time interval. 24 work agents are managed by a cooperative agent that would coordinate the solutions of the work agents. The relationship among all the agents is shown in **Error! Reference source not found.**.

As shown in the figure, except relating with the coordination agent every work agent had information exchanged with the previous and following adjacent work agents. Each work agent is responsible for coordinating the static scheduling of wind power, thermal units and PHEVs, their relationship is shown in Figure 4. Its goal is the minimum of fuel consumption and emissions in this period, the constraints are static for the corresponding time interval, without considering the dynamic time coupling constraints. Then the genetic algorithm is used. The target of the cooperative agent is the minimum of cost and emissions for the whole scheduling cycle, the constraints are the dynamic coupling constraints on the entire scheduling period.

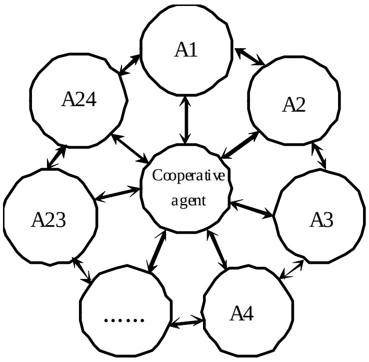

Figure 3. MAS Architecture of the Smart Grid Optimal Dispatching

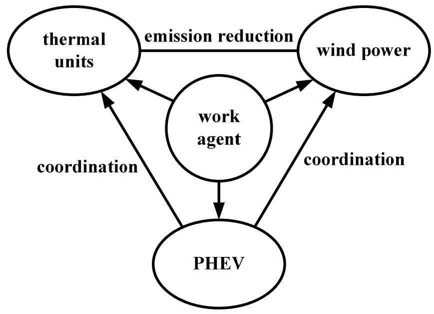

Figure 4. The Work Agent Synergistic Effect Diagram

4. Numerical Example

An independent system operator of 10-unit system is considered for simulation with wind power and 50000 PHEVs. Load demand and unit characteristic of the 10-unit system are collected from [18]. Assume the reserve to be 10% of the load demand. It is necessary to integrate wind in the sustainable smart grid to reduce cost and emission. The amount of cost and emission reductions mainly depends on maximum utilization of renewable energy through PHEVs. PHEVs are charging/discharging intelligently so that both cost and emission are minimum. Load demand and constraints are fulfilled. Maximum battery capacity=25kWh, minimum battery capacity=10kWh, average battery capacity=15kWh, maximum number of charging/discharging PHEVs at each hour, $N_{v2G}^{\max t}$ =10% total PHEVs. Total number of PHEVs in the system, $N_{v2G}^{\max}$ =50000. Charging-discharging frequency=1 per day; scheduling period=24h, departure state of charging/discharging Ψ =50%, efficiency ξ =85%. A PHEV needs 8.22kWh/day, an excess of 8.22*50000=411MWh power will be needed for the smart grid [19]. And the wind farm can provide 500MWh/day energy. A typical day forecasts of wind are given in [20]. This paper analyzes two cases, one does not consider the uncertainty of load and wind power, the other considers the uncertainty of load and wind power for smart grid.

1) Cost-emission reduction dispatching without the uncertainty of load and wind power

Cost-emission reduction weights can give decision-makers the intuitive analysis of the concerned factors. The effect of the weight changes on the optimization scheduling is analyzed below.By this way, it verifies the effectiveness of the cost-emission reduction model.

CO_2 is one of the main discharge in the electric power production process, it has a significant impact on the environment. The relationship of thermal cost-emission objectives and weights without/with PHEVs can be seen in Table 1, 2.

Table 1. The Relationship of Thermal Cost-emission Objectives and Weights without PHEVs

weights / objective	(1,0)	(0.9, 0.1)	(0.8, 0.2)	(0.7, 0.3)	(0.6, 0.4)	(0.5, 0.5)	(0.4, 0.6)	(0.3, 0.7)	(0.2, 0.8)	(0.1, 0.9)
F/$	562877.68	565223.52	565277.32	566047.70	567142.24	569650.16	571398.77	573509.10	574978.12	580665.09
E_c/t	269906.39	258751.20	258511.43	256140.50	254110.02	251107.34	249687.99	248611.43	248061.91	247206.69

Table 2. The Relationship of Thermal Cost-emission Objectives and Weights with PHEVs

weights / objective	(1, 0)	(0.9, 0.1)	(0.8, 0.2)	(0.7, 0.3)	(0.6, 0.4)	(0.5, 0.5)	(0.4, 0.6)	(0.3, 0.7)	(0.2, 0.8)	(0.1, 0.9)
F/$	558296.90	558820.94	563374.18	566955.17	570939.72	576805.18	585359.22	595455.63	601028.84	627416.16
E_c/t	273326.41	265999.73	239229.49	228502.65	221747.58	214312.78	206959.47	202141.48	200350.52	197259.18

From Table 1 and 2, the weight factors of cost and emission are (1,0), (0.9,0.1), (0.8,0.2), (0.7,0.3), (0.6,0.4), (0.5,0.5), (0.4,0.6), (0.3,0.7), (0.2,0.8), (0.1,0.9) respectively. With the weight factor of the operation cost ω_c decreasing, cost is increasing, but the variation is small which can be accepted. Increasing the weight factor ω_e, CO_2 emission can be reduced substantially. When (ω_c, ω_e) is (0.8,0.2), the operation cost is 563374.18$, CO_2 emission is 239229.49t (Table 2). On the other hand, when PHEVs are not considered in the same system, the operation cost is 565227.32$, CO_2 emission is 258511.43t in the same system (Table 1). PHEVs save 1853.14$ and reduce 19281.94t emission. Compared with Table 1, CO_2 emissions substantially reduce in Table 2 with others weights. It shows that the scheduling with PHEVs can effectively reduce the difference between peak and valley power system, save costs and reduce emission, increase the comprehensive benefit in the 10-unit thermal system. By choosing proper weight factors of cost and emission on the basis of the decision-makers' willingness, satisfactory scheduling results of coordinating cost and emission can be reached.

The relationship of smart grid cost-emission objective and weights with PHEVs and wind power is shown in Table 3. PHEVs optimal charge/discharge power under the deterministic load and wind power with weights (0.9, 0.1) is shown in Figure 5

Table 3. The Relationship of Smart Grid Cost-emission Objectives and Weights with PHEVs and Wind Power

weights / objective	(1, 0)	(0.9, 0.1)	(0.8, 0.2)	(0.7, 0.3)	(0.6, 0.4)	(0.5, 0.5)	(0.4, 0.6)	(0.3, 0.7)	(0.2, 0.8)	(0.1, 0.9)
F/$	548891.79	549546.20	554252.04	557302.88	562802.51	570160.03	572150.96	580846.21	600041.87	616846.89
E_c/t	272720.36	260372.43	232846.27	223181.17	213111.80	206424.36	204699.40	200816.72	195108.10	193441.20

Effect of both cost and emission in the deterministic model with PHEVs and wind power is shown in Table 3. Compared with Table 2, in the same weights of costs and emission, the operation costs and emission are rapidly decreasing (Table 3); cost is reduced by 9122.14$, and emission is reduced by 6383.22t in the weight of (0.8,0.2) (Table 3). Compared with Table 1, cost is reduced rapidly, emission increases slowly ((1,0), (0.9,0.1)); the cost is reduced by 11025.28$, the emission is reduced by 25665.15t ((0.8,0.2)) . Both the cost and emission are reduced in Table 3 than those of Table 1 and 2. Proper using of PHEVs and wind power, PHEVs can charge from the grid with wind power at off-peak hours and discharge to the grid at peak hours, which are complementary for each other.

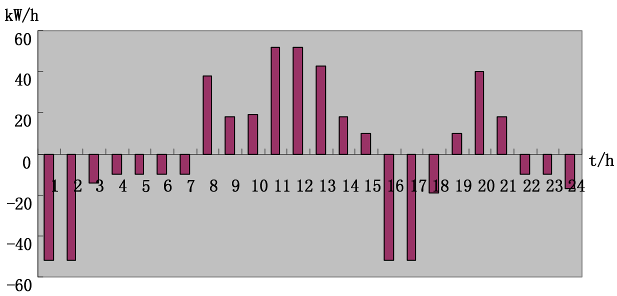

Figure 5. PHEVs Optimal Charge/Discharge Power under the Deterministic Load and Wind Power

As you can see from Figure 5, PHEVs charging in the low load period, in the peak load stage discharge, charge/discharge power through effective control of PHEVs, can realize the minimization of cost-emission in the smart grid.

2) Cost-emission reduction dispatching considering the uncertainty of load and wind power

The relationship of cost-emission objectives and weights with the uncertainty of PHEVs/PHEVs and wind power can be seen in Table 4 and Table 5. PHEVs optimal charge/discharge power under the uncertainty of load and PHEVs with the weights (0.9, 0.1) is shown in Figure 6.

Table 4. The Relationship of Thermal Cost-emission Objective and Weights with the Uncertainty of PHEVs

weights / objective	(1,0)	(0.9,0.1)	(0.8,0.2)	(0.7,0.3)	(0.6,0.4)	(0.5,0.5)	(0.4,0.6)	(0.3,0.7)	(0.2,0.8)	(0.1,0.9)
F/$	578223.53	578936.68	582329.60	586481.65	592218.67	599284.96	605292.07	615894.74	636482.46	647222.85
E_c/t	280108.44	268564.82	248920.36	236654.97	225603.96	217572.76	212967.85	206250.55	202943.65	198771.44

Table 5. The Relationship of Cost-emission Objective and Weights with the Uncertainty of PHEVs and Wind Power

weights / objective	(1, 0)	(0.9, 0.1)	(0.8, 0.2)	(0.7, 0.3)	(0.6, 0.4)	(0.5, 0.5)	(0.4, 0.6)	(0.3, 0.7)	(0.2, 0.8)	(0.1, 0.9)
F/$	568647.30	569399.55	573136.83	577366.93	582508.40	589849.29	596051.48	598441.91	617921.86	635898.43
E_c/t	274933.62	263843.80	242164.38	229576.25	219953.49	211218.50	206218.27	205242.61	198209.91	196459.40

Table 4 shows the results of cost and emission when only PHEV is considered, similarly Table 5 shows the results of costs and emission when both PHEV and wind power are considered. Compared with the results of Table 4, the cost and emission are cut with the same weights (Table 5). Wind power saves 9192.77$, and reduces 6755.98t with the weight (0.8,0.2). Because of the uncertainty, the system cost and emissions are increased, but it is closer to the actual situation.

PHEVs can reduce dependencies on small expensive units in existing systems, resulting in reduced operation cost and emission. It can also increase reserve and reliability of existing power systems.

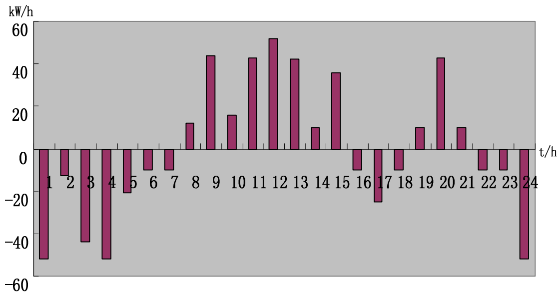

Figure 6. PHEVs Optimal Charge/Discharge Power under the Uncertainty of Load and Wind Power

5. Conclusion

Wind power and PHEV grid-connected capacity expansion has become an inevitable trend, will exert a far-reaching influence on power system. To bring the opportunity to power grid cost-emission reduction operation, random and load demand and output of wind power has increased the difficulty of scheduling.

The optimal scheduling with wind power, PHEVs and conventional thermal units under uncertainty is presented in this paper to illustrate cost and emission reductions. The uncertainty of wind power and load, PHEVs charge/discharge control, the coordination of PHEVs and wind power is considered. The multi-scenario simulation is used for accommodating the volatility of wind power and load. Then the MAS is used to generate a successful schedule. It contains 24 work agents in the scheduling period. Each work agent uses genetic algorithm to produce a solution set for the time interval. Wind power, PHEVs and thermal units are coordinated. 24 work agents are managed by a cooperative agent that would coordinate the solutions of the work agents. Valid scenarios are derived from prior statistics, heuristics and the experience. The results show that the algorithm is an efficient approach and the solution is reasonable. This optimization with uncertainties for scheduling needs more cost and longer execution time; however, it is more reliable in real environment.

Acknowledgements

This work is supported by National Natural Science Foundation of China (Grant No: 51207074) and the project of Jiangsu Key laboratory of power transmission & distribution equipment technology (Grant No: 2011JSSPD10).

References

[1] Lunz B, Yan ZX, Gerschler JB, et al. Influence of plug-in hybrid electric vehicle charging strategies on charging and battery degradation costs. *Energy polic.* 2012; 46: 511-519.
[2] Parks K, Denholm P, Markel T. *Costs and emissions associated with plug-in hybrid electric vehicle charging in the xcel energy Colorado service territory.* Colorado: National Renewable Energy Laboratory. 2007.
[3] Saber AY, Venayagamoorthy GK. Intelligent unit commitment with vehicle-to-grid-A cost-emission optimization. *Journal of Power Sources.* 2010; 195(1): 898-911.
[4] Hadle SW, Tsvetkova A. Potential impacts of plug-in hybrid electric vehicles on regional power generation. ORNL/TM-2007/150. 2008.
[5] K Meyer, KK Schneider, R Pratt. Impacts assessment of plug-in hybrid vehicles on electric utilities and regional U.S. power grids part 1: Technical analysis. *Pacific Northwest Laboratory.* 2007.
[6] Zhong WZ, Hao Y, Ying LL .Parametric matching of drivetrain for parallel hybrid electric vehicle. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013; 11(10): 5789-5796.
[7] Islam FR, Pota HR. PHEVs Park as Virtual UPFC. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(8): 2285-2294.
[8] Sioshansi R, Fagiani R, Marano V. Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system. *Energy policy.* 2010; 38: 6703-6712.
[9] NREL, plug-in hybrid electric vehicles and wind energy. Available: http://www.nrel.gov/analysis/winds/pdfs/wind_phev_poster.pdf
[10] Willett K, Jasna T. Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy*. Journal of Power Sources*. 2005; 144(1): 280-294.
[11] Henrik L, Willett K. Integration of renewable energy into the transport and electricity sectors through V2G. *Energy Policy*. 2008; 36(9): 3578-3587.
[12] Wang J, Liu C, Ton D, et al. Impact of plug-in hybrid electric vehicles on power systems with demand response and wind power. *Energy policy.* 2011; 39(7):4016-4021.
[13] Lisa G, Sten K, Filip J. Integration of plug-in hybrid electric vehicles in a regional wind-thermal power system. *Energy Policy.* 2010; 38(10): 5482-5492.
[14] Soares MC, Bruno B, Alexandre S, et al. Plug-in hybrid electric vehicles as a way to maximize the integration of variable renewable energy in power systems: The case of wind generation in northeastern Brazil. *Energy*. 2012; 37(1): 469-481.
[15] Liu C, Wang JH, Botterud A, et, al. Assessment of impacts of PHEV charging patterns on wind-thermal scheduling by stochastic unit commitment. *IEEE Transactions on Smart Grid*. 2012; 3(2): 675-683.
[16] Khodayar ME, Wu L, Shahidehpour M. Hourly coordination of electric vehicle operation and volatile wind power generation in SCUC. *IEEE Transactions on Smart Grid*. 2012; 3(3): 1271-1279.
[17] Venkatesh P, Gnanadass, Padhy NP. Comparison and application of evolutionary programming techniques to combined economic emission dispatch with line flow constraints. *IEEE Transactions Power Systems*. 2003; 18(2): 688-697.
[18] Ongsaku W, Petcharaks N. Unit commitment by enhanced adaptive lagrangian relaxation. *IEEE Transactions on power systems*. 2004; 19(1): 620-628.
[19] Saber AY, Venayagamoorthy GK. Intelligent unit commitment with vehicle-to-grid-A cost-emission ptimization. *Journal of Power Sources*. 2010; 195(1): 898-911.
[20] Ahmed YS, Venayagamoorthy GK. Resource scheduling under uncertainty in a smart grid with renewables and plug-in vehicles. *IEEE system Journal*. 2012; 6(1): 103-109.