A Contract-Based Pricing Scheme for the Renewable Energy Trading

Shina Xu[1,2], Jingli Mao[1], and Biling Zhang[1,2]
[1] School of Network Education, Beijing University of Posts and Telecommunications, P. R. China.
[2] The State Key Laboratory of Integrated Services Networks, Xidian University, P. R. China.
Email: {na101912, mjl018}@126.com; bilingzhang@bupt.edu.cn

Abstract —The renewable energy generating terminals (REGTs)not only have capability to generate electricity for them own usage but also have surplus electricity to sell to the Power Grid (PG). However, the REGTs are generally self-interested. Due to the diversity in their supply capacity, REGT shave different preferences toward selling electricity, which is the private information and unknown to the PG. In such a case, how to stimulate different REGTs to participate the trade under the information asymmetry is a very important problem. In this paper, a novel contract-based pricing scheme is proposed for the electricity trading stimulation. To find the optimal pricing scheme, i.e., the optimal contract, an interior-point based algorithm is proposed. With the optimal contract, the PG is able to fulfill its power demand with least payment while the REGTs can obtain the maximal utilities by selecting the contract item of their own types. Simulation results are shown to verify the effectiveness of the proposed contract-based pricing mechanism. Compared to other pricing schemes, our proposed pricing scheme outperforms in incenting REGTs to sell their surplus electricity to meet the demand of PU.

Index Terms—Electricity trading, information asymmetry, contract theory, incentive mechanism, pricing scheme

I. INTRODUCTION

With communication, monitoring, control and other intelligent device being integrated into Power Grid (PG) [1]-[3], smart grid is emerging as the next-generation power grid which urges smart electronic equipment and advanced management methods [4]-[6] into an integrated power system.

In the smart grid, to offload the traffic and decrease the loss in the process of long-distance transmission and distribution from power plant to end user, electricity from nearby distributed energy units such as electricity battery and domestic renewable generating device is desirable and will form a significant part of the power supply [7], [8]. However, the renewable energy generating terminals (REGTs) vary in their ways and capabilities of energy generation, and thus have different preferences in the electricity trading. Since the REGTs are all rational and selfish in reality, they only care about their profits and will not participate in the trade if the trading cannot bring them any benefit. In such a case, for the PG which would like to collect power from these REGTs, how to stimulate the REGTs to sell their surplus electricity is an important problem. Nevertheless, the preference is the REGTs' private information unknown to the PG, which make the stimulation problem more challenge.

In the recent literatures, lots of pricing based incentive mechanisms have been proposed for stimulating cooperation of electricity supply and demand [9], [10]. For example, the authors in [9] presented discrete optimization models that provide day-ahead pricing plans to manage time-of-day (TOD) residential electricity loads in a retail setting, taking into account the time substitutability of TOD demand as well as the time-dependent customer response to price incentives. While in [10] the authors proposed a demand elasticity scheme where the price elastic behaviors of aggregated loads are modeled as a set of multi-dimensional demand-price. In the previous work, however, the preference diversity of REGTs is not considered and all REGTs are just regarded equally, making the existing incentive schemes less available in the aforementioned renewable energy trade scenario.

Another category of cooperation stimulation schemes is game based schemes [11], [12]. In [11], a non-cooperative game-theoretic approach is proposed to build a novel double-auction market model between the smart grid and storage units, in which storage units could strategically decide the amounts they put up for sale conditioning on the current market state and their own production states. While in [12], the authors formulated a direct trading interactions of end-users who act as small-scale electricity suppliers into a coalitional game, where revenue obtained by the group is fairly divided among group members through asymptotic Shapley value. In most of the existing works, game theoretic frameworks for smart grids are based on a complete information assumption, i.e., the players in the game know all the necessary information of trading and the information between both sides of the transaction are symmetric. However, such an assumption is not true in reality.

As a well-developed mathematical tool that is effective in designing incentive compatible mechanisms under the circumstance of asymmetric information, contract theory has been used to successfully tackle the cooperation stimulation problems in wireless communication [13], cognitive radio networks [14], and distributed computing

Manuscript received June 8, 2016; revised September 26, 2016.
This work was supported by the Foundation Natural Science Foundation of China (No.61501041） and Open Foundation of State Key Laboratory (No. ISN16-08).
Corresponding author email: bilingzhang@bupt.edu.cn.
doi:10.12720/jcm.11.9.848-855

[15]. In the context of smart grid, an optimal contract is designed to offer incentives for electricity vehicles to provide ancillary services to the aggregator [16].

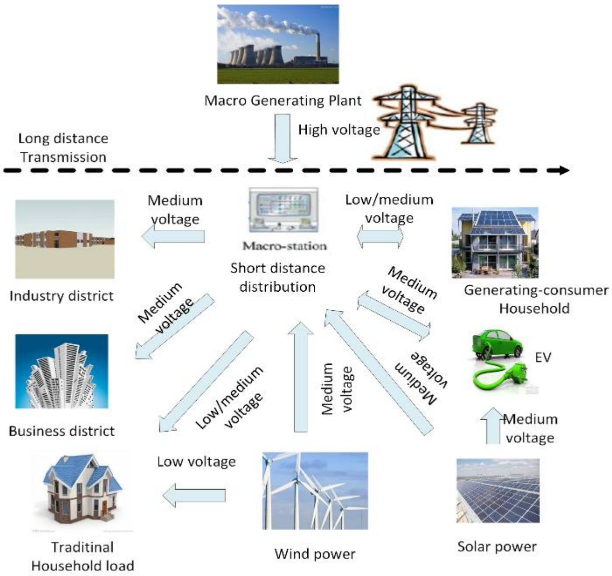

Fig. 1. The scene of system model.

Therefore, in this paper, we propose to design an incentive mechanism for renewable energy trading based on contract theory. Different from existing mechanisms where the contract is designed by a seller [16], we discuss the trading stimulation problem from the perspective of buyers. To characterize the REGT's preference, several factors are taken into account, based on which the utility function of both the REGT and the PG are defined. The interactions of the PG and REGTs are then formulated into the framework of game. In the game, we simplify the necessary and sufficient conditions of the constraints, and then propose an interior-point based algorithm to find the optimal contact. With the optimal contract, the PG not only attracts self-interested REGTs to provide electricity, but also maximizes its own revenue. Meanwhile, the REGTs obtain the maximal utilities by selecting the contract items of their own types. Compared with the traditional schemes, our contract-based incentive mechanism is more effective and can be implemented efficiently.

The rest of this paper is organized as follows. Section II describes our system model in details. In Section III, we introduce the feasible condition and convenient solution to the optimal contract. Finally, we show the simulation results in Section IV and draw conclusions in Section V.

II. System Modeland Problem Formulation

As shown in Fig. 1, we assume that there are M REGTs who have surplus electricity and the PG would like to collect this electricity for its nearby power end users, especially in the peak time. In such a way, the traffic can be offloaded from the PG and the loss in the process of long distance transmission and distribution from power plant to end user can be avoided. As a reward, the PG will offer the REGTs with a certain pay.

Note that REGTs can be various in capabilities of power supply due to the difference of power generating device type, electricity usage, battery capacity and level, and so on. However, such information is private to the REGTs and unknown to the PG. On the other hand, REGTs are self-interested and only care about how to maximize their own utilities, while the PG has no direct control on the selling action of REGTs. In such a case, how to encourage the REGTs to take part in the trade and act cooperatively is a necessary issue for the PG.

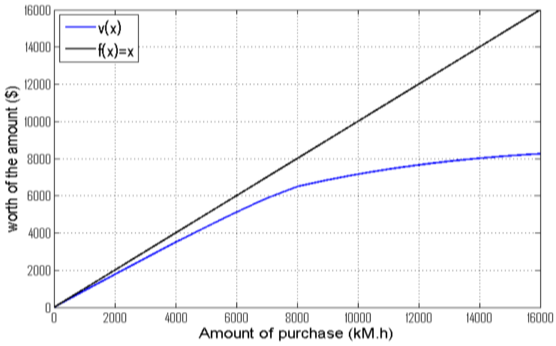

Fig. 2. The shape of function *v(x)*.

Taking the information asymmetry into consideration, we propose a contract-based incentive approach. With the optimal design of contract, not only PG but also REGTs can get a maximal utility from the energy trade. In the following section, we describe trading model in details for the PG, (i.e., the buyer) and REGTs (i.e., the sellers) and how their interactions are formulated into the framework of a contract game.

A. *The Model of the PG*

The PG is in charge of designing the contract and claims it to the REGTs before the transaction. The item of the contract is described as $(x, p(x))$, where $x$is the amount of power the PG wants to buy and $p(x)$ is the unit price that the PG can pay. With the transaction $(x, p(x))$, the PG's utility can be calculated as

$$U_{PG}(x,p) = v(x) - xp \tag{1}$$

where $v(x)$ is the PG's benefit after obtaining x units of power. Without loss of generality, $v(x)$ is assumed to be a non-decreasing concave function of x, i.e., $v'(x) \geq 0$, $v''(x) \leq 0$ in the feasible region. In this paper, $v(x)$ is defined as $v(x) = p_r(x)\cdot x$, where

$$p_r(x) = \left(1 - \frac{h(x) + \sum_{i=1}^{4} a_i n_i [h(x)/n_i](h(x)\% n_i)}{kn_1 + h(x)}\right) \tag{2}$$

Here, $h(x) = \log_2(2+x)$, $n_i = \log_2(2 + D\cdot\sqrt{i}/2)$,D represents the amount of electricity PG want to purchase via the trade. Beside, operator [·] means getting the integral data, while operator % represents mod calculation. Moreover, k and a_i are parameters that can affect the rate of change of $p_r(x)$. As we can see in Fig. 2, the function $v(x) = p_r(x)x$ matches the characters that $v^{'}(x) \geq 0,\ v^{''}(x) \leq 0$, in the feasible region (purchasing demand D is 8000kW.h, other parameters k=7, a_1=0.2, a_2=0.2, a_3=0.6, a_4=1.2).

B. The Model of REGTs

The REGTs, who are sellers in the transaction with the PG, will provide their surplus electricity if they have. Let E_1, E_2 and E_3 be a REGT's power generation output, consumption and current battery storage, respectively. Then $\Delta E = E_1 - E_2$ will be its excessive electricity which is used to characterize the REGT's capacity in power supply. Since REGTs' capacity in power supply is different from each other and the power supply capacity is REGTs' private information, in this paper, REGTs are categorized into N types according to ΔE, i.e., $\Delta E_1, \cdots, \Delta E_N$ .Considering the convenience of analysis, we assume that $\Delta E_1 < \Delta E_2 < \cdots < \Delta E_N$.

The diversity in the REGTs' power supply capacity also leads to the difference in the unit cost in offering electricity. For the i^{th} type REGT who sells $x$units power to the PG, the unit cost function can be calculated as

$$c_i(x) = \begin{cases} 0, & x \leq 0 \\ C_1, & 0 < x \leq \Delta E_i \\ C_1 + (1 - \Delta E_i / x) C_2, & 0 < \Delta E_i < x \\ C_1 + C_2, & \Delta E_i \leq 0 < x \end{cases} \quad (3)$$

where C_1 is the average cost of generating a unit electricity, and C_2 is the average cost of charging-discharging battery. Here,we assume that C_1 and C_2 are the same for all the REGTs, which are known to both of the PG and REGTs. From (3) we have Lemma 1.

Then in the energy trade, given the contract items $\phi = \{(x_1, p(x_1)), \cdots, (x_N, p(x_N))\}$, the utility of the i^{th} type REGT can be defined as

$$u_i(x, p) = x \cdot (p - c_i(x)). \quad (4)$$

C. Contract-based Problem Formulation

Recalling that REGTs can be various with different capabilities in power providing. For the PG who would like to maximize its own utility, it should design different contract items for different types of REGTs.

Suppose the contract item for the i^{th} type REGT be $(x_i, p_i(x_i))$. To make sure that the REGTs have motivation to accept the contract and take part in the electricity trade, $(x_i, p_i(x_i))$ should satisfy the individual rationality (IR) constraint, i.e., $u_i(x_i, p_i) = x_i\left(p_i - c_i(x_i)\right) \geq 0$, $i \in \{1, \cdots, N\}$ .The IR constraint ensures that the reward REGT gets from the PG must compensate its cost in generating power. Otherwise, REGT will not accept the contract but signs a special contract of $(0, p(0))$ where $p(0) = 0$ and gains a zero utility, i.e., $u_i(0,0) = 0$.

On the other hand, to make sure that the REGTs will not hide their type and get a maximal utility for reward by accepting the contract item for its type, that is, the i^{th} type REGT just prefer the contract item $(x_i, p_i(x_i))$ rather than other items $(x_j, p_j(x_j)),\ j \neq i$, the contract should also satisfies the incentive compatibility (IC) constraints. According to the IC constraints.

In such a case, the optimal contract designing problem for the power trading is formulated into the following optimization problem.

$$\max: U_{PG}(x, p) = v\left(\sum_{i=1}^{N} \lambda_i \cdot x_i\right) - \sum_{i=1}^{N} \lambda_i \cdot x_i p_i$$

$$\begin{aligned} \text{s.t.} \quad & \text{(a)}\ x_i \cdot \left(p_i - c_i(x_i)\right) \geq 0, \\ & \text{(b)}\ x_i \cdot \left(p_i - c_i(x_i)\right) \geq x_j \cdot \left(p_j - c_i(x_j)\right), \\ & \text{(c)}\ \Delta E_1 < \Delta E_2 < \cdots < \Delta E_N, \\ & \text{(d)}\ 0 < x_i \leq \Delta E_i + E_{i3}, i, j \in \{1, \cdots, N\}, i \neq j. \quad (5) \end{aligned}$$

In (5), (a) and (b) represent the IR and IC constraints respectively while (c) represents the monotonicity condition. The problem in (5) is not a convex optimization problem which can be solved with regular methods, but can be resolved by the algorithm proposed in the following section.

III. The Optimal Strategies

To simplify the problem in (5), we first introduce four Lemmas which is useful for finding the optimal solutions.

Lemma 1: $\forall i \in \{1, \cdots, N\}$, $c_i(x)$ is a non-decreasing function of x with the maximum of $C_1 + C_2$.

Proof: 1) If $\Delta E_i \leq 0$, then $\forall x \in (0, \Delta E_i + E_{i3})$, which is a non-decreasing function of x.

2) If $\Delta E_i > 0$, then for $0 < x \leq \Delta E_i$, we have $c_i(x) = C_1 < C_1 + C_2$ which is also a non-decreasing function of x.

3) For $\Delta E_i < x \leq \Delta E_i + E_{i3}$, we have $c_i(x) = C_1 + (1 - \Delta E_i / x) \cdot C_2 < C_1 + C_2$, which is a monotonically increasing function with respect to x.

To summarize, $c_i(x)$ is a non-decreasing function with the maximum of $C_1 + C_2$.

Lemma 2: For $\Delta E_1 < \Delta E_2 < \cdots < \Delta E_N$, there is $c_1(x) \geq c_2(x) \geq \cdots \geq c_N(x)$.

Proof: 1) If $0 < \Delta E_1 < \Delta E_2 < \cdots < \Delta E_N$, when $x \in (0, \Delta E_1]$, we have $c_1(x) = c_2(x) = \cdots = c_N(x) = C_1$.

When $x > \Delta E_1$, we have $c_1(x) > c_2(x) \ge \cdots \ge c_N(x) \ge C_1$.

2) If $\Delta E_1 < \Delta E_2 < \cdots < \Delta E_N \le 0$, then $\forall x > 0$, we have $c_1(x) = c_2(x) = \cdots = c_N(x) = C_1 + C_2$.

3) If $\Delta E_1 < \cdots < \Delta E_i < 0 < \Delta E_{i+1} < \cdots < \Delta E_N$, when $x \in (0, \Delta E_{i+1}]$, we have $c_1(x) = \cdots = c_i(x) = C_1 + C_2 > c_{i+1}(x) = \cdots = c_N(x) = C_1$. Otherwise, $x > \Delta E_{i+1}$, we have $c_1(x) > c_2(x) \ge \cdots \ge c_N(x) \ge C_1$.

To summarize, the conclusions established.

Lemma 3: For all the types of REGTs selling electricity, the optimal amount of electricity they should sell satisfies $x_1^* < x_2^* < \cdots < x_N^*$. Here, x_i^* is the optimal amount of electricity the i^{th} type REGT should sell.

Proof: For $\Delta E_i < \Delta E_{i+1}$, let $x_i^* = \arg\max u_i(x, p)$, and $x_{i+1}^* = \arg\max u_{i+1}(x, p)$.

Since $c_i(x_i^*) \ge c_{i+1}(x_i^*)$, we have $x_i^*\left(p_i - c_i(x_i^*)\right) < x_i^*\left(p_i - c_{i+1}(x_i^*)\right)$. In such a case, if $x_i^* > x_{i+1}^*$, then for the i^{th} REGT, we have $x_{i+1}^*\left(p_{i+1} - c_i(x_{i+1}^*)\right) < x_i^*\left(p_i - c_i(x_i^*)\right)$, which contradicts with the IC constraints. Since $x_i^* \ne x_{i+1}^*$, that must have $x_i^* < x_{i+1}^*$, which results in $x_1^* < x_2^* < \cdots < x_N^*$.

With Lemma 1, Lemma 2 and Lemma 3, we can simplify the constraints in (5) as stated in Lemma 4 by following similar steps proposed in [17].

Lemma 4: Assuming $\Delta E_1 < \Delta E_2 < \cdots < \Delta E_N$, the constraints in (5) can be reduced as

(a) $x_1 \cdot \left(p_1 - c_1(x_1)\right) = 0$,

(b) $x_i \cdot \left(p_i - c_i(x_i)\right) = x_{i-1} \cdot \left(p_{i-1} - c_i(x_{i-1})\right)$,

(c) $\Delta E_1 < \Delta E_2 < \cdots < \Delta E_N$,

(d) $0 < x_i \le \Delta E_i + E_{i3}, i \in \{1, \cdots, N\}$.

Proof: **Step 1:** There are N IR constraints in (5), however, they can be cut down as long as finding the rule behind.

$$x_N \cdot (p_N - c_N(x_N)) \ge x_{N-1} \cdot (p_{N-1} - c_N(x_{N-1})) \ge$$
$$x_{N-1} \cdot (p_{N-1} - c_{N-1}(x_{N-1})) \ge \cdots \ge x_1 \cdot \left(p_1 - c_1(x_1)\right) \ge 0$$

The intermediate inequality can be set up because of lemma 2.

As shown above, when the lower type of RGES obey the IR constraints, the higher types will satisfy automatically.

Step 2: For N REGTs, there are N(N-1) IC constraints in the (5). But, it's likely to reduce these redundant constraints too.

Firstly, two local downward incentive constraints (LDIC) can be gotten from the IC conditions in (5).

$$x_i \cdot \left(p_i - c_i(x_i)\right) \ge x_{i-1} \cdot \left(p_{i-1} - c_i(x_{i-1})\right) \quad (6)$$

$$x_{i-1} \cdot \left(p_{i-1} - c_{i-1}(x_{i-1})\right) \ge x_{i-2} \cdot \left(p_{i-2} - c_{i-1}(x_{i-2})\right) \quad (7)$$

In (7), replace $c_{i-1}(x_{i-1})$, $c_{i-1}(x_{i-2})$ with $c_i(x_{i-1})$ and $c_i(x_{i-2})$ respectively, referring to appendix A, the increment of two sides conform to:

$$x_{i-1} \cdot [c_{i-1}(x_{i-1}) - c_i(x_{i-1})] \ge x_{i-2} \cdot [c_{i-1}(x_{i-2}) - c_i(x_{i-2})]$$

Then (7) can be replaced by the following formula:

$$x_{i-1} \cdot \left(p_{i-1} - c_i(x_{i-1})\right) \ge x_{i-2} \cdot \left(p_{i-2} - c_i(x_{i-2})\right) \quad (8)$$

as $c_i(x_{i-1}) \le c_{i-1}(x_{i-1})$, a formula can be produced after putting (6) and (8) together:

$$x_i \cdot \left(p_i - c_i(x_i)\right) \ge x_{i-2} \cdot \left(p_{i-2} - c_i(x_{i-2})\right) \quad (9)$$

By the same token:

$$x_i \cdot \left(p_i - c_i(x_i)\right) \ge x_k \cdot \left(p_k - c_i(x_k)\right), 1 \le k \le i-3. \quad (10)$$

For i^{th} type REGT, these IC constraints in (9) and (10) are also called downward incentive constraints (DIC), which can be cut down too because of their inherent redundancy.

Similarly, two local upward incentive constraints (LUIC) can be gotten from the IC conditions in (5).

$$x_i \cdot \left(p_i - c_i(x_i)\right) \ge x_{i+1} \cdot \left(p_{i+1} - c_i(x_{i+1})\right) \quad (11)$$

$$x_{i+1} \cdot \left(p_{i+1} - c_{i+1}(x_{i+1})\right) \ge x_{i+2} \cdot \left(p_{i+2} - c_{i+1}(x_{i+2})\right) \quad (12)$$

In (12), replace $c_{i+1}(x_{i+1})$、$c_{i+1}(x_{i+2})$ with $c_i(x_{i+1})$ and $c_i(x_{i+2})$, referring to appendix A, the increment of two sides conform to:

$$x_{i+1} \cdot [c_{i+1}(x_{i+1}) - c_i(x_{i+1})] \ge x_{i+2} \cdot [c_{i+1}(x_{i+2}) - c_i(x_{i+2})]$$

then (12) can replaced by the following formula:

$$x_{i+1} \cdot \left(p_{i+1} - c_i(x_{i+1})\right) \ge x_{i+2} \cdot \left(p_{i+2} - c_i(x_{i+2})\right) \quad (13)$$

as $c_i(x_i) \le c_{i+1}(x_i)$, aformula can be produced after putting (11) and (13) together:

$$x_i \cdot \left(p_i - c_i(x_i)\right) \ge x_{i+2} \cdot \left(p_{i+2} - c_i(x_{i+2})\right) \quad (14)$$

Similarly:

$$x_i \cdot \left(p_i - c_i(x_i)\right) \ge x_k \cdot \left(p_k - c_i(x_k)\right), i+3 \le k \le N \quad (15)$$

For i^{th} type RGES, these IC constraints in (14) and (15) are also called upward incentive constraints (UIC), which can be cut down too.

Step 3: So far, there are N-1 LDICs and N-1 LUICs remain in the IC constraints. It's not difficult to find that these LDICs and LUICs are intersection condition with each other, which means the IC constraints can be cut down again.

Just ignoring the LUICs and intensively, considering LDICs and monotonicity of the cost function, if objective function gets the optimal value, all the LUICs will be tight. Otherwise,

$$x_i \cdot (p_i - c_i(x_i)) > x_{i-1} \cdot (p_{i-1} - c_i(x_{i-1}))$$

For $j \geq i$, PG can adjust the contract until the constraints tight to increase the value of objective function by lowering p_j without affecting other LUICs.

Under the premise that all the LDICs is tight, then

$$x_i \cdot (p_i - c_i(x_i)) = x_{i-1} \cdot (p_{i-1} - c_i(x_{i-1})),$$

$$c_i(x_{i-1}) \leq c_{i-1}(x_{i-1})$$

means that

$$x_i \cdot (p_i - c_{i-1}(x_i)) \leq x_{i-1} \cdot (p_{i-1} - c_{i-1}(x_{i-1})) \text{(LUIC)}$$

holds, in other words, LUICs can be cut down too. Therefore, there are N-1 LDICs remained in the IC constraints

With Lemma 4, the problem formulated in (5) can be re-written as:

$$\max: U_{PG}(x, p) = v\left(\sum_{i=1}^{N} \lambda_i \cdot x_i\right) - \sum_{i=1}^{N} \lambda_i \cdot x_i p_i$$

s.t.

(a) $x_1 \cdot (p_1 - c_1(x_1)) = 0$,

(b) $x_i \cdot (p_i - c_i(x_i)) = x_{i-1} \cdot (p_{i-1} - c_i(x_{i-1}))$,

(c) $\Delta E_1 < \Delta E_2 < \cdots < \Delta E_N$,

(d) $0 < x_i \leq \Delta E_i + E_{i3}, i \in \{1, \cdots, N\}$ (16)

Obviously, the problem shown in (6) is also a nonlinear-constraint optimization problem. To find the optimal solutions, data such as the average generating cost C_1, average storage cost C_2, ΔE in a time slot according to previous trade information, then an interior-point based algorithm, i.e., algorithm I, is proposed in this section.

ALGORITHM 1: FING THE OPTIMAL CONTRACT USING INTERIOR-POINT

---

1. Select a feasible non-zero initial value $\phi^0 = \{(x^0, p^0)\}$.
   - Definite linear inequality constraints $x_1 < x_2 < \cdots < x_N$.
   - Define the bound of ϕaccording to input data.
   - Explicit the original value of penalty factor r^0.
   - Confirm convergence criterion and precision ε.
   - Determine coefficient of diminution $\beta \in (0,1)$.
2. Dowhile ($\varepsilon^k > \varepsilon$)
   - Structure penalty function $\varphi(\phi, r^k) = -U_{PG}(\phi) + r^k H(\phi)$ and calculate x^k and p^k with method of SUMT.
   - Calculate $\varepsilon = \left| \dfrac{\varphi(\phi^k, r^k) - \varphi(\phi^{k-1}, r^{k-1})}{\varphi(\phi^{k-1}, r^{k-1})} \right|$.
   - Replace initial value with extremal point $x^0 \leftarrow x^k$ $p^0 \leftarrow p^k$.
   - Narrow the penalty factor $r^{k+1} \leftarrow \beta r^k$.

End

In practice, if PG needs a certain amount of electricity from REGTs, it firstly confirms the purchasing quantity, then classifies the types of REGT by estimating the relation between the purchasing quantity and total electricity (gotten by previous trade information), and extracts the distribution of each type of REGT, i.e., λ_i with $\sum_{i=1}^{N} \lambda_i = 1$. Next, using Algorithm 1, PG designs the optimal contract and broadcasts it to all the REGTs. The REGT selects one of the items among ϕ or rejects the contract (do not participate the trade this time). If the REGT signs the contract with the PG, it will provide a certain amount of power as promised and get a paid as reward from the PG.

IV. SIMULATION RESULTS AND ANALYSIS

In this section, the feasibility of our proposed contract based scheme is testified and its performance is analyzed. In the simulation, we consider a scenario that includes M=1000 REGTs. The average cost of generating a unit electricity C_1 is set to 0.5 and the average cost of charging-discharging battery C_2 is set to 0.1. In the parameters in equation (2) are set as k=7, a_1=0.2, a_2=0.2, a_3=0.6, and a_4=1.2.

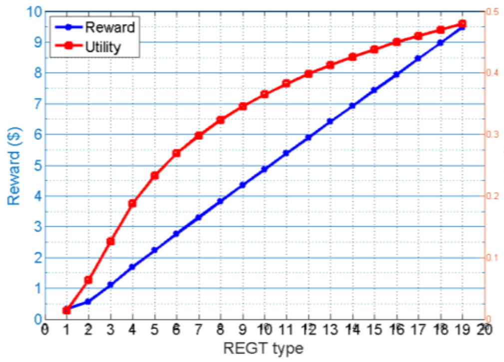

Fig. 3. REGT's reward and utility.

We first verify the feasibility of our proposed contract based scheme and the results are shown in Fig. 3 and Fig. 4. From Fig. 3 we can see that the rewards and utilities of the REGTs are always positive whenever they participate the trade, implying that our scheme satisfies the IR constraints and the REGTs have incentive to sell their surplus electricity to PG. From Fig. 4, we can see that the REGTs can obtain the maximal utility only when they select the contract items designed for their own types (the i^{th} REGT selects the i^{th} contract item, taking the type of

5^{th}, 10^{th} and 15^{th} REGTs for example). This means our scheme also satisfies the IC constraints, and the hidden information of REGTs is revealed truthfully.

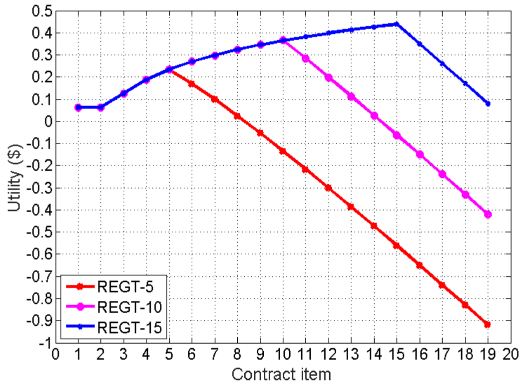

Fig. 4. REGT's Utilities with different contract items

Next, we verify the performance of our proposed scheme by comparing it with three other existing pricing schemes, i.e., the single pricing scheme (the price is constant no matter how much amount of electricity the REGT want to trade with PG), the descending pricing scheme and the ascending pricing scheme (these two pricing scheme provide 5 different prices according to trading amount of electricity with descending or ascending trend). In this work, the performance of the schemes are verified in terms of the maximum utility of PG (remarked as PG Utility), the total amount of electricity the PG can buy from the REGTs (remarked as sumAmount), the total money the PG should pay (remarked as totalPayment), the sum of REGTs' utility (remarked as SumUtility), and the average unit price (unitPrice) and the profit or utility that unit payment brings to PG (remarked as and unitProfit) to represents the economic efficiency about the trading. All these parameters are shown together in the special histogram with their own respective units.

Fig. 5 shows the results of the case where the PG's demand is less than the amount the REGTs can supply, i.e., the PG's demand is 4,200 kWh while total ΔE of all REGTs is 7,643 kWh. Although the PG's demand can be fulfilled with all the four pricing schemes, adopting our proposed scheme, the PG obtains the most amount of electricity with the lest payment, and thus obtains the lowest average unit price and the highest profit that unit payment brings to it. This is because in our proposed scheme the power supply capacity as well as the production cost as private information has been taken into consideration and the IR and IC rules are fully obeyed. In such a way, the REGTs are encouraged to sell their energy at the lowest price. While in other schemes, without take the private information into consideration, the PG always pays the REGTs at the price that higher than their margin cost of the electricity, and thus results in a higher payment for the same amount of power.

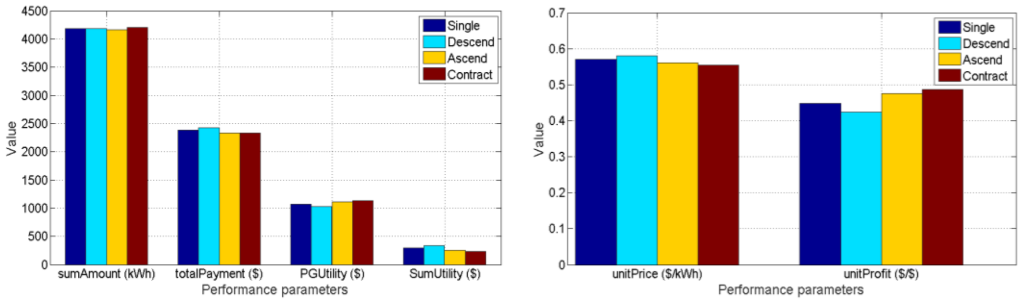

Fig. 5. The PG's demand is 4,200 kWh, and total ΔE of all REGTs is 7,643kWh.

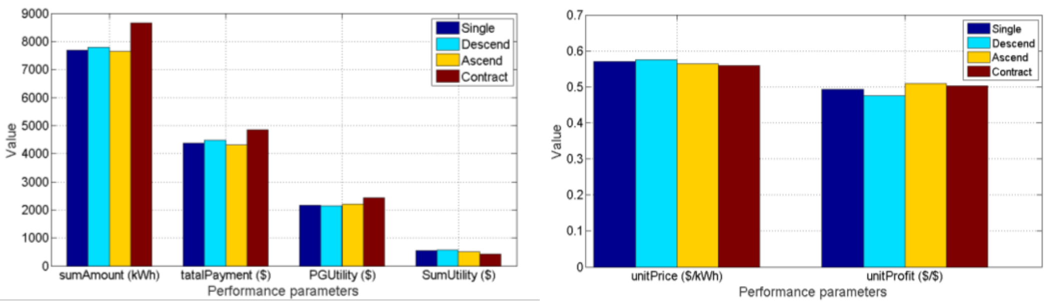

Fig. 6. The PG's demand is 10,000 kWh, and total ΔE of all REGTs is 7,643 kWh.

Fig. 6 shows the results of the case where the PG's demand is larger than the amount the REGTs can supply, i.e., the PG's demand is 10,000kWh while ΔE of all REGTs is 7,643kWh. In this case, none of the four scheme can fulfill the power demand, because it is not economical for REGT to sell more electricity to PG from their battery with a high cost. However, PG with our proposed scheme is able to procure more electricity than the other pricing schemes due to its incentive mechanism.

V. Conclusion

In this paper, we propose a novel contract based cooperation incentive scheme to efficiently encourage the REGTs to sell their excessive renewable energy to the PG, especially in the peak time. To find the optimal contract, an interior-point based algorithm is proposed. With the optimal contract, REGTs are motivated to truthfully select the item corresponding their types and gain the maximal utilities, while the PG is able to buy enough energy to fulfill the power demand with the minimum payment. Simulation results verify the effectiveness of our scheme, and prove that our proposed scheme outperforms the existing flat pricing schemes.

APPENDIX A

For $\Delta E_i < \Delta E_j < \Delta E_k$, if $x_i < x_j$, then $x_j \cdot [c_j(x_j) - c_k(x_j)] \ge x_i \cdot [c_j(x_i) - c_k(x_i)]$.

Proof: for (1) $0 < x_i < x_j < \Delta E_j < \Delta E_k$, then,

$$x_j \cdot [c_j(x_j) - c_k(x_j)] = 0, \quad x_i \cdot [c_j(x_i) - c_k(x_i)] = 0.$$

(2) $0 < x_i \le \Delta E_j < x_j \le \Delta E_k$, then,

$$x_j \cdot [c_j(x_j) - c_k(x_j)] = (x_j - \Delta E_j)C_2,$$
$$x_i \cdot [c_j(x_i) - c_k(x_i)] = 0.$$

(3) $0 < \Delta E_j < x_i < x_j \le \Delta E_k$, then,

$$x_j \cdot [c_j(x_j) - c_k(x_j)] = (x_j - \Delta E_j)C_2,$$
$$x_i \cdot [c_j(x_i) - c_k(x_i)] = (x_i - \Delta E_j)C_2.$$

(4) $0 < \Delta E_j < x_i \le \Delta E_k < x_j$, then,

$$x_j \cdot [c_j(x_j) - c_k(x_j)] = (\Delta E_k - \Delta E_j)C_2,$$
$$x_i \cdot [c_j(x_i) - c_k(x_i)] = (x_i - \Delta E_j)C_2.$$

(5) $0 < \Delta E_j < \Delta E_k \le x_i < x_j$, then,

$$x_j \cdot [c_j(x_j) - c_k(x_j)] = (\Delta E_k - \Delta E_j)C_2,$$
$$x_i \cdot [c_j(x_i) - c_k(x_i)] = (\Delta E_k - \Delta E_j)C_2.$$

(6) $\Delta E_j \le 0 < x_i < x_j \le \Delta E_k$, then,

$$x_j \cdot [c_j(x_j) - c_k(x_j)] = x_j C_2, \quad x_i \cdot [c_j(x_i) - c_k(x_i)] = x_i C_2.$$

(7) $\Delta E_j \le 0 < x_i \le \Delta E_k < x_j$, then,

$$x_j \cdot [c_j(x_j) - c_k(x_j)] = \Delta E_k C_2, \quad x_i \cdot [c_j(x_i) - c_k(x_i)] = x_i C_2.$$

(8) $\Delta E_j \le 0 < \Delta E_k < x_i < x_j$, then,

$$x_j \cdot [c_j(x_j) - c_k(x_j)] = \Delta E_k C_2, \quad x_i \cdot [c_j(x_i) - c_k(x_i)] = \Delta E_k C_2.$$

(9) $\Delta E_j < \Delta E_k \le 0 < x_i < x_j$, then,

$$x_j \cdot [c_j(x_j) - c_k(x_j)] = 0, \quad x_i \cdot [c_j(x_i) - c_k(x_i)] = 0.$$

From what has been discussed above, the proposition sets up.

ACKNOWLEDGMENT

This paper was partly funded by National Natural Science Foundation of China (No.61501041) and Open Foundation of State Key Laboratory (No. ISN16-08).

REFERENCES

[1] Z. M. Fadlullah, M. Fouda, N. Kato, A. Takeuchi, N. Iwasaki, and Y. Nozaki, "Toward intelligent machine-to-machine communications in smart grid," *IEEE Commun. Mag.*, vol. 49, no. 4, pp. 60–65, 2011.

[2] H. Liang, B. J. Choi, A. Abdrabou, W. Zhuang, and X. Shen, "Decentralized economic dispatch in microgrids via Heterogeneous wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 6, 2012.

[3] M. Fouda, Z. M. Fadlullah, N. Kato, R. Lu, and X. Shen, "A lightweight message authentication scheme for smart grid communications," *IEEE Trans. Smart Grid*, vol. 2, no. 4, pp. 675-685, 2011.

[4] P. Nyeng and J. Ostergaard, "Information and communications systems for control-by-price of distributed energy resources and flexible demand," *IEEE Transactions on Smart Grid*, vol. 2, no. 2, pp. 334-341, 2011.

[5] J. Ma, J. Deng, L. Song, and Z. Han, "Incentive mechanism for demand side management in smart grid using auction," *IEEE Transactions on Smart Grid*, vol. 5, no. 3, pp. 1379-1388, 2014.

[6] P. Wang, L. Rao, X. Liu, and Y. Qi, "D-pro: Dynamic data center operations with demand-responsive electricity prices in smart grid," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1743-1754, 2012.

[7] W. Saad, Z. Han, and H. V. Poor, "Coalitional game theory for cooperative micro-grid distribution networks," in *Proc. IEEE International Conference on Communications Workshops*, 2011, pp. 1-5.

[8] S. Chakraborty, S. Nakamura, and T. Okabe, "Scalable and optimal coalition formation of microgrids in a distribution system," in *Proc. Innovative Smart Grid Technologies Conference Europe*, 2014, pp. 611-618.

[9] S. Subramanian, S. Ghosh, J. Hosking, R. Natarajan, and X. Zhang, "Dynamic price optimization models for managing time-of-day electricityusage," *IEEE Smart. Grid. Comm.*, Oct. 2013.

[10] R. Yu, W. Yang, and S. Rahardja, "A statistical demand-price model with its application in optimal real-time price," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1734-1742, Dec. 2012.

[11] Y. Wang, W. Saad, Z. Han, and H. V. Poor, "A game-theoretic approach to energy trading in the smart grid," *IEEE Transactions on Smart Grid*, vol. 5, no. 3, pp. 1439-1450, 2014.

[12] W. Lee, L. Xiang, R. Schober, and V. W. S. Wong, "Direct electricity trading in smart grid: a coalitional game analysis," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 7, pp. 1398-1411, 2014.

[13] Y. Zhang, L. Song, W. Saad, Z. Dawy, and Z. Han, "Contract-Based incentive mechanisms for device-to-device communications in cellular networks," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 10, p. 1, 2015.

[14] S. P. Sheng and M. Liu, "Profit incentive in trading nonexclusive access on a secondary spectrum market through contract design," *IEEE/ACM Transactions on Networking*, vol. 22, no. 4, pp. 1190-1203, 2014.

[15] L. Duan, L. Gao, and J. Huang, "Cooperative spectrum sharing: A contract-based approach," *IEEE Transactions on Mobile Computing*, vol. 13, no. 1, pp. 174-187, 2014.

[16] Y. Gao, Y. Chen, C. Y. Wang, and K. J. R. Liu, "Optimal contract design for ancillary services in vehicle-to-grid

networks," in *Proc. IEEE Third International Conference on Smart Grid Communications*, 2012, pp. 79-84.
[17] P. Bolton and M. Dewatripont, *Contract Theory*, Ulb Institutional Repository, vol. 1, no. 1, pp. 83–101, 2005.

Shina Xu received the B.S. degree from the Xi'an University of Posts and Telecommunications (XUPT), Xi'an, China, in 2013. He is currently pursuing the M.S. degree with the Information and communications professional in Beijing University of Posts and Telecommunications (BUPT), Beijing, China. His research interests include smart grid, wireless communication and communication network.

Biling Zhang received the B.S., M.S. and Ph.D. degrees from Beijing University of Posts and Telecommunications (BUPT), Beijing, China, in 2000, 2003 and 2013, respectively. She is currently an Associate Professor of BUPT. Her main research interests are smart grid, cognitive radio networks, wireless communication and cooperative communication.

Jingli Mao Her main research interests are smart grid, communication network and wireless communication.