A Comparative Study on Pricing Rules and Its Effect on Total Dispatch Cost

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Abstract

A focus of study in auction market design is revenue comparison. Revenue Equivalence Theorem implies that bidders receive the same amount of revenue invariant to the auction type. This paper explores the applicability of this theorem in the context of the electricity market. We develop experimental test cases using agent-based simulation to examine the impact of different pricing rule on total dispatch cost. Using Q-learning in a repetitive trading environment, generator agents can quickly learn the market characteristics and seek to maximize their revenue by adapting their bidding strategies. A look-up table is utilized as a learning mechanism to improve the agent’s bidding strategies. We conclude that Revenue Equivalence Theorem holds in a multi-unit-multi-period in symmetric bidding. In asymmetric bidding and when the market share of generator agents differs significantly, the computer simulation allows us to observe the rapid increase in revenue with uniform auction.

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Keywords: vickrey auction; dispatch cost; competitive market; strategic bidding; electricity market

1. Introduction

Research in Economics reported that there is no significant difference in the market performance between the Uniform and Pay-as-Bid pricing rule. The theory underpinning the research in [1, 2] is the Revenue Equivalence Theorem (RET). The theorem, as cited in [3] stated that “Suppose bidders have independent and identically distributed valuations and are risk neutral. Then any symmetric and increasing equilibrium of a direct revelation auction that assigns the item to the highest bidder such that the expected payment of bidder with value zero is zero, yields the same expected revenue.” However, RET only applies where a single unit of an indivisible good is being auctioned, in a single-period setting. In electricity market, auctions may take place with asymmetric bidding in the context of multi-unit, multi-period arrangement. Moreover, the applicability of RET in the context of the electricity market assumes that all generators bid with identical strategies and are risk neutral. In reality, instead of being risk neutral and bidding identically, generators behave differently to maximise its expected profit according to their

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understanding of the market environment [4-6]. Furthermore, many studies in this topic, such as [1] and [2], were based on mathematical analysis and did not reflect the highly dynamic characteristics of a real time competitive electricity market. Study in [7] stated that the Uniform pricing rule causes poor performance in terms of market price, generator’s revenue and total dispatch cost. Pay-as-Bid rule has been proposed as an alternative [8]. However, other contradictory results have also been reported in the literature in terms of the impact of pricing rules on generator’s revenue, market price and price volatility brought by these two pricing rules [9-12]. While the argument over comparing these two pricing rules has lasted decades in the electricity market establishment process, little attention has been paid to the Vickrey pricing rule [13], despite being perceived to be highly favourable by economists [1].

Based on the foregoing, we wish to investigate the applicability of RET using an agent based simulation model. Specifically, we wish to examine the bidding behaviour of the generator agents and to evaluate the impact of different auction types on generators profit. Further, it should be noted that in the proposed models documented in previous studies, generators were often assumed to submit bid quantity at their maximum capacity. Such bid quantity was either accepted completely or not at all. In our study, we propose a model which allows generators to submit any amount of bid quantity up to its maximum generating capacity. In short, this paper reports our experiment using agent-based model to investigate the implication on total dispatch cost when employing Uniform and Vickrey pricing rule in a simplified competitive electricity market.

2. Agent-based Model

In the past decade, there has been an increasing number of studies that employed agent-based simulation models to study market power of electricity markets, for example studies documented in [4, 14-16]. In [4], an agent-based simulation in a coordination game was used to explore the possibility of market abuse in a competitive electricity market. Based on the England and Wales electricity markets, the model investigated whether or not two cooperating generators could profitably influence wholesale prices. In [16], an agent-based computational model was used to study the market power and efficiency of electricity markets with discriminatory double-auction pricing. The study found that active bidding by buyers would limit the ability of sellers to exercise market power.

A popular learning algorithm called Q-Learning is employed as the learning method for the agents. Q-learning is a Reinforcement Learning technique that works by learning an action-value function that gives the expected utility of taking a given action in a given state and following a fixed policy thereafter. The entities modelled with Q-Learning can behave in such a way that they are able to use their past experience to improve their behaviour [17]. It was proposed by Watkins [18] for solving the Markovian Decision problems with incomplete information. The main advantage of Q-Learning algorithm is that it is model-free and can be used on-line to find an optimal result based on the direct interaction with the environment. This feature makes it suitable for decision making problems in repeated games with unknown component [19].

3. The Proposed Simulation Model

Figure 1 illustrates the proposed electricity market model with Q-Learning based generator. In a competitive electricity market, generators submit bids in each trading period. The bid price that a generator can offer is between its marginal cost and the price cap set by the ISO, whereas the bid quantity is between its minimum stable load and its max capacity. This is shown in Equations (1) and (2).

\[ mc_g \leq P_g \leq P_{cap} \] (1)

\[ \text{min} Q_g \leq Q_g \leq \text{max} Q_g \] (2)

where \( mc_g \) is the marginal cost of a competing generator; \( P_g \) and \( Q_g \) are the bid price and bid quantity submitted by a competing generator; \( P_{cap} \) is the price cap set by the ISO; \( \text{max} Q_g \) is the maximum quantity that can be offered by a competing generator.

ISO schedules the actual dispatch starting from the generator offering the lowest bid price, following the bid stacking method. This process is terminated until all the demand is fulfilled:

\[ \sum Q_g = \text{Demand} \] (3)

Competing for dispatch, generators always adopt profit maximising strategy. If Uniform rule is employed, the single market clearing price is the last bid price accepted by the ISO, calculated as:

\[ \text{Profit}_g = (MCP - mc_g) \times \text{Dispatch}_g \] (4)
where \( MCP \) is the market clearing price; \( \text{Dispatch}_g \) is the actual dispatch for a competing generator scheduled by the ISO. When Vickrey pricing rule is employed, the generator will be paid based on the opportunity cost its presence introduces to all the other generators. Therefore, the generator’s profit is calculated as:

\[
\begin{align*}
\eta_{total} &= \sum_{a \in A} p_g \cdot \text{Dispatch}_g \\
\eta_{total'} &= \sum_{a \in A} p_g \cdot \text{Dispatch}_g \\
\eta_{other} &= U_{total} - P_g \cdot \text{Dispatch}_g \\
U_{other}' &= U_{total'} \\
R_g &= U_{other}' - U_{other} \\
\text{Profit}_g &= R_g \cdot mc_g \cdot \text{Dispatch}_g
\end{align*}
\]

where \( \eta_{total} \) is the total utility received by all the generators when generator \( g \) is competing for dispatch; \( \eta_{other} \) is the total utility received by all the other generators when generator \( g \) is competing for dispatch; \( \eta_{total'} \) (or \( \eta_{other}' \)) is the total utility received by all the generators when generator \( g \) is excluded from competition; \( R_g \) is the revenue received by generator \( g \).

The state is defined as the bid price and quantity pair each generator submitted in previous trading period. For each generator, there are \( N-1 \) main intervals equally defined. \( N-1 \) is the number of quantity selections that can be chosen by a generator where each selection represents a bid quantity range. Within each main interval, there are \( M-1 \) sub-intervals equally defined. \( M-1 \) is the number of price selections that can be chosen by a generator in which each selection represents a bid price range. \( N \) and \( M \) is calculated as follow:

\[
\begin{align*}
N &= \max Q_g - \min Q_g \quad (11) \\
M &= P_{\text{cap}} - 0 \quad (12)
\end{align*}
\]

The increments for both main interval and sub-interval in each main interval are set to 1. Therefore, there are \( N-1 \) times \( M-1 \) sub-intervals in total with each representing a selected bid price and quantity pair.

The definition of action is the same as state except that the calculation of \( M \) and \( N \) are modified as follows:

\[
\begin{align*}
N &= \max Q_g - \min Q_g' \quad (13) \\
M &= P_{\text{cap}} - mc_g \quad (14)
\end{align*}
\]

Simulated Annealing (SA)-Q-Learning algorithm [20] has been adopted as the action selection policy:

1) Randomly select an action \( a_r \), where \( a_r \in A \).
2) Adopt greedy approach: select action \( a_p \), where \( a_p \in A \).
3) Generate a random number \( \text{rand} \) between 0 and 1.
4) Select the final action based on the following calculation:

\[
a = \begin{cases} 
    a_p, & \text{rand} \geq \exp \left[ \frac{Q(s, a_r) - Q(s, a_p)}{\text{temperature}} \right] \\
    a_r, & \text{otherwise}
\end{cases}
\]

5) Update the temperature parameter based on pre-defined temperature dropping function.

The temperature dropping function, as defined in [20], is suggested as follow: Assume \( T_n \) is the temperature in the \( nth \) iteration, then \( T_n = \beta T_{n-1} \), where \( n \) is natural number and \( \beta \) is a constant number close to 1 to ensure a slow decay of the temperature in the algorithm. \( T_1 \) is set to 100000 and \( \beta \) is defined as 0.999 based on trial-and-error.

The bid quantity of each generator in each trading period is constrained by its ramp rate, which is:
where $Q_g$ and $Q'_g$ are the bid quantity in current and previous trading period accordingly, $R_g$ is the ramp rate.

The immediate reward is the profit of each generator in each trading period, calculated using either (4) or (10) depending on which pricing rule is employed. The simulation is run as follows:

1) Initialize a Q-value table for each generator.
2) For each trading period:
   a) Agents submit bids, select action and next state.
   b) ISO collects all the bids and schedule the dispatch.
   c) Agents receive their profit based on pricing rule.
   d) Update Q-value table for each agent according to:

$$Q(s, a) \leftarrow (1 - \alpha) Q(s, a) + \alpha [r + \gamma \max Q(s', a')]$$

where $s' \leftarrow s'$.

The learning rate is denoted with $\alpha$, where $0 \leq \alpha \leq 1$; the discount factor is denoted with $\gamma$, where $0 \leq \gamma \leq 1$. The learning rate in this paper is designed to be state action dependent as in [19, 21], which is inversely proportional to the visited number of a particular state-action pair up to the present trading period. The learning rate $\alpha$ for a state-action pair $k$ is calculated as $\alpha_k = 1/N_k$, where $N_k$ is the number of times that this pair $k$ have been taken by a generator. The discount factor $\gamma$ in this paper is assigned with the value of 0.1. This value leads to a short reaction time for the generator agents to respond to the change in the market due to their recent-reward pursuing which makes their behaviour easier to be captured and analysed.

4. Case Study

Three cases have been prepared to study the agent behaviour. Each case includes four competing generator agents with similar attributes, namely the same minimum stable load, ramp rate and production cost. The aggregated (or total) supply capacity of the four generators is fixed. In the three cases, the maximum generating capacity of generator agent 1 is set to: 25% of aggregated supply capacity in case 1, 50% of aggregated supply capacity in case 2, and 75% of aggregated supply capacity in case 3. The total demand is set to approximately 60% of aggregated supply capacity. In addition, a backup generator with extremely large capacity and high price (reserve capacity price) is set for each case to ensure the demand can still be fulfilled even if the total supplied quantity by the four competing generators is less than the demand. For each case, two scenarios are tested. In the first scenario, the agent must submit bid that offers the maximum generating capacity; while in the second scenario, the generator agent can submit bid quantity following its profit maximizing strategy. This means, in the second scenario, generator agent may offer less than its maximum available capacity when it considers this as a strategic bid. In addition, these scenarios are tested for different pricing rule: (1) economic dispatch based on Uniform pricing, and (2) economic dispatch based on Vickrey pricing rule.

In each simulation cycle, the total dispatch cost is calculated by taking the average of the total dispatch costs in the last 10,000 trading periods to allow sufficient exploration and exploitation periods. We then use the total dispatch cost under Uniform pricing rule in Case 1, Scenario 1 as a factor to normalise the other results. By doing so, the value for the total dispatch cost under Uniform pricing rule is 1. This way, the effect of different pricing rules and supply quantity variation on total dispatch cost can be examined.

5. Discussion of Results

**Case 1**

<table>
<thead>
<tr>
<th>Total Dispatch Cost</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Uniform</td>
<td>Vickrey</td>
</tr>
<tr>
<td>Case 1</td>
<td>1</td>
<td>1.1</td>
</tr>
<tr>
<td>Case 2</td>
<td>5.69</td>
<td>2.67</td>
</tr>
<tr>
<td>Case 3</td>
<td>5.69</td>
<td>6.55</td>
</tr>
</tbody>
</table>

Figure 2: Simulation results

As can be seen in Figure 2 (Scenario 1, Case 1), the total dispatch costs are comparable under both pricing rules. In this case, all generators have the same attributes but offering different bid price. Therefore, it can be generalised
that all four generator agents exhibit similar bidding behaviour. This situation somewhat satisfies the requirements over which the RET holds, yielding the same total dispatch cost for these generators. In short, RET holds in this situation.

In Scenario 2, bid quantity has been added as another variable in the simulation. The approach for each generator to develop their bidding strategy becomes unpredictable. A generator can develop its bidding strategy by altering both its bid price and bid quantity. This leads to a variation in the agents’ bidding strategies. Under this circumstance, the Vickrey pricing rule leads to a slightly higher dispatch cost.

In comparing Scenario 1 and Scenario 2, allowing variable bid quantity may lead to an increase in the total cost.

Case 2

In this case (refer to Figure 2), when bidding at maximum capacity is required, it is observed that the total cost under Uniform pricing rule is much higher than under Vickrey. This is because the maximum generating capacity of generator agent 1 is at 50% of total supply capacity (on par with the aggregated supply capacity of the others). In Uniform rule, it is as if three agents form a coalition in competing with the first generator agent; yet, the three generator agents can bid more flexible by being able to supply three different bids. This cooperative behaviour among the three generator agents is unfavourable to the first generator agent. As a result, in order to get higher profit, it is observed that the first generator has to bid at a much higher price (even close to the cap price) to recover its loss in dispatch. This high market clearing price leads to a high total dispatch cost.

Under Vickrey pricing rule, due to the large generating capacity of generator agent 1 (50% aggregated supply capacity), even if it submits the highest bid price among all the players, at least 10% supply will need to be dispatched from its capacity. When its revenue is calculated by excluding generator agent 1, such supply shortage will have to be fulfilled by the backup generator. This may still lead to large revenue as calculated by (9) due to the extremely high reserve capacity price. For the three small generators, in order to get satisfactory revenue, that is, the opportunity cost introduced to others from its presence, the small generator has to ensure enough dispatch quantity so that the \( U_{other} \) does not equal to \( U_{total} \) which otherwise leads to a zero revenue. This requirement can only be reached by lowering the bid price since neither of the small generators can incur a supply shortage due to its small capacity. Hence, it is observed that the bid prices of the three agents are close to their production cost. As a result, only a small amount of dispatch will be paid at a very high price which significantly lower the total dispatch cost.

In Scenario 2, when bid quantity can vary, under Uniform rule, the large generator can strategically limit its maximum supply quantity comparable to the other three small generators. This results in a highly reduced profit difference when compared with Scenario 1. Here we observe the supply capacity withholding phenomenon - an opportunity for any generator agent to withhold its capacity to draw the backup generator into the market. Even though this means that the three small generators will be scheduled, the extremely high reserved capacity price enables the quantity-withholding generator agent to gain high profit from satisfying the unfulfilled demand. This behaviour leads to extremely high market clearing price and therefore total dispatch cost in some trading periods.

Under Vickrey pricing rule, allowing variable bid quantity also increases the chance of supply capacity withholding phenomenon. However, unlike Uniform pricing, only generator agent 1 has been observed to withhold supply capacity. For a reason similar to Scenario 1, only a small portion of dispatch is paid at a high price which therefore retains a comparatively low total dispatch cost comparing to it under Uniform pricing rule.

Case 3

The last case study (refer to Figure 2) depicts a situation where a large generator has a clearly dominant position in the market. All the other three agents have very limited supply capacity to fulfil the market demand. Due to this, generator agent 1 can easily overcome the unfavourable collusion among the three small generators and gain the highest revenue. More importantly, its dominant position makes it the market price setter controlling the clearing price as the cap price in scenario 1 and the reserved capacity price in Scenario 2. Accordingly, the total dispatch costs under these two scenarios are both very high; and the total cost is even higher when bid quantity can vary.

Under Vickrey pricing rule, the situation is similar as in Case 2. However, due to the increased size of generator agent 1, more shortage needs to be fulfilled if generator agent 1 is excluded. As a result, revenue gained by generator 1 and the total dispatch cost increase substantially.

There is another emergence observed in Case 3. In Case 2, it is noted that the total dispatch cost under Uniform is higher than it is under Vickrey in both scenarios. However, in Case 3, the total dispatch cost under Uniform pricing is only higher than Vickrey when bid quantity is made variable. This is because when maximum capacity is supplied, under Uniform pricing rule, there is no chance to draw the backup generator to the market which therefore limits the maximum price to be the cap price. However, when Vickrey pricing is adopted, as described before, the
shortage caused by excluding the large generator from the competition will need to be fulfilled by the backup generator. As a result, this remarkably increases the total dispatch cost.

6. Conclusion

From the case studies, it can be concluded that in symmetric bidding, the RET still holds even in a multi-unit, multi-period auction setting, as depicted in Case 1, Scenario 1. The RET does not hold in asymmetric bidding. When bidding at maximum capacity is required and there is a dominant player, it is observed that the Uniform pricing rule significantly suffers from the unfavorable collusion behavior and the single market clearing price. Under Vickrey rule, the total dispatch cost also increases as the dominant player’s capacity increases. In Case 3, this total dispatch cost exceeds that under Uniform rule. A much lower total dispatch cost in Case 2 indicates that this phenomenon is observable only when the capacity of a dominant player becomes excessive. In conclusion, it can be argued that Vickrey pricing is better than the Uniform pricing in terms of controlling the total dispatch cost when bid at maximum capacity is required. The comparison between these two pricing rules is shown in Figure 3 (left).

Figure 3: Total dispatch cost for fixed bid quantity (left) and variable bid quantity (right)

REFERENCES