FLEXIBLE FORWARD CONTRACTS FOR RENEWABLE ENERGY GENERATORS IN DEREGULATED ELECTRICITY MARKETS

Zamiyad Dar, Koushik Kar and Aparna Gupta

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1 Introduction

The amount of renewable energy in the United States has increased considerably in the last ten to fifteen years. Most of this increase is attributed to the addition of wind and solar power [1]. In 2014, renewable electricity accounted for more than 50% of U.S. electricity capacity additions [2]. Both wind and solar are highly intermittent sources [3]. The amount of wind power from a windfarm can change significantly with rapidly changing wind speeds. The variability of wind power in the United States has been discussed in detail in [4]. The highly volatile nature of wind power also presents an obstacle in integrating this zero-cost power source in the day-ahead electricity markets.

There is some research on the subject of forward contracts for windfarms to sell their volatile energy in the day-ahead or forward contract markets. In [5], constant values for penalty and reward are introduced for deficit and surplus, and windfarm power is divided between firm and risky power for forward contracting purpose but real time prices are not part of the contract. In [6], a payment sharing mechanism is proposed for multiple windfarms to participate in the day-ahead market while penalty and reward for deficit and surplus are treated as random variables. In [7] and [8], a new mechanism is proposed where wind farms bid probability distributions of generation, instead of bidding cost functions and an aggregator chooses the wind power to be supplied in the market but such mechanism are not permitted with present regulations in the electricity markets. In [9], a bilateral contract for fixed load is proposed for the whole year in which windfarm has to supply fixed amount of quantity at each hour of the year in exchange for a predetermined price for each hour. Other papers dealing with forward contracts for windfarms include [10–13].

In this paper, we make use of the increasing amounts of flexible loads in power system to introduce flexible forward contracts for windfarms. Flexible loads such as electric cars, washing machines, HVAC systems can move their demand between certain hours and only require a certain amount of energy within a relatively flexible time period. The flexibility of these loads can allow windfarms to engage in bilateral forward contracts and enable them to distribute their intermittent energy supply amongst different time periods depending on the wind conditions. We propose a flexible contract which allows the windfarm to deviate from the committed power amounts in the day-ahead market as long as certain constraints on energy and flexibility are met. One such example would be that the windfarm is allowed to deviate from the committed amount in the contract as long as it provides some specified amount of total energy at different time intervals.

The flexible load considered in this paper is electric vehicles but our formulations can be easily extended to other types of flexible loads as well. We consider two types of flexibilities in the load. The first type of flexibility is the total amount of energy required by each car. Second type of flexibility is the flexibility in the starting times at which the load will begin to receive the power from the windfarm. These flexibilities in energy and time allow the windfarm to deviate from the committed amounts in the forward contract if there is a difference between forecasted and actual wind generation or forecasted and actual real time price. This type of flexible contract would also provide the windfarm with a choice to sell its electricity in the real time market instead of providing the committed amount for day-ahead contract in case there is a price spike in real time market. Since the windfarm gains advantages in terms of the flexibility in the contract and benefits from the real time price spikes, the transaction price of such flexible forward contracts should be set at a level less than the day-ahead market price.

The novel contributions in our work are two folds. First, we propose a new forward contracting mechanism for windfarms in which windfarms are allowed to deviate from their contracted supply amounts in the day-ahead market. We achieve this by having the windfarms make this contract with flexible loads such as electric cars. This allows the windfarms to move the contracted power amounts among different time intervals as long as they meet certain cumulative energy requirements at certain time intervals. The flexible contract proposed in this research also does not require any additional changes in the existing electricity market structure, such as addition of penalty functions for supply deficit or reward amounts for oversupply.

Second, we also show the difference in profits of a windfarm if it made a simple forward contract with fixed amounts of supply versus the profits of the windfarm using the proposed flexible forward contract. This additional profit would incentivize both parties in the contract to reduce the contract transaction price below the day-ahead market price. We do this for seven days of a week, using real time price and real time wind generation data, both belonging to the same region of New York state.

The rest of this paper is organized as follows. In Section 2, we propose the flexible contracting mechanism. We describe the simulation setup in Section 3. In Section 4, we show and explain the results of simulating the flexible contract for windfarms for seven days of a week. Section 5 concludes and summarizes the paper.

2 Formulation of flexible forward contracts

With the increase in the amount of flexible loads (e.g., electric vehicles) and introduction of demand response programs, there is a new incentive for a power supplier with an intermittent power source (like a windfarm owner) to engage in a forward contract which allows it to deviate from the contracted amount in case of power unavailability, shortage or excess due to unexpected wind conditions. We propose such a flexible contract in this section and also calculate the financial value of the incentive for this flexible contract in later sections.

2.1 Fixed forward contract

First we discuss the generally existing fixed forward contracts between a windfarm and a load entity. We assume that these contracts are taking place in the day-ahead deregulated markets. Let us consider a windfarm with a maximum power rating ρ_{max}. We make the following assumptions regarding the windfarm:

1. We assume that the windfarm is a price taker and ρ_{max} is small enough compared to the market size so that the windfarm does not affect the real-time price.

2. We also assume that the amount of wind energy integration in the system is not abundant and low or high wind conditions do not affect the electricity prices.

3. Windfarm is assumed to have a zero marginal cost of production.

We consider a two tier deregulated electricity market structure (which is common in many states), run by an Independent System Operator (ISO) such as NYISO, ISONE, CAISO etc. ISO collects the bids for generation, regulation and load demand from market participants for the day-ahead and real-time markets. The data for the day-ahead market including day-ahead price at each interval of the day, load forecast etc. is released 12 to 24 hours in advance [14]. In the real-time or spot market, ISO is responsible for balancing the load and generation. ISO purchases extra generation, initiates demand response or redirects dispatch if needed in the real-time. Based on these situations, ISO releases the real-time market prices which are usually different than the day-ahead market prices.

Let us consider that the day-ahead price for hour t of the next day is given as Day_t and is known to every market participant. Suppose the windfarm enters into a fixed forward contract (bilateral or with ISO) in the day-ahead market to provide ρ_t units of power at time t. Since it is a fixed forward contract, the windfarm is obligated to supply the ρ_t units of power at time t regardless of the amount of its available power generation.

In case, the windfarm produces less than ρ_t units (due to poor wind conditions), the ISO or windfarm can purchase the shortfall in the spot (real-time) market at the real-time prices and thus the windfarm will have to bear a per unit cost equal to the difference between the day-ahead (contract) price and the real-time (spot market) price. On the other hand, if the wind conditions are better than expected and the windfarm has more than ρ_t units of power, it can sell the surplus in the real-time market at the real-time price.

If $Wind_t^r$ is the realized wind power at time t and $Real_t^r$ is the real-time price at time t, then the windfarm payoff function for this fixed forward contract will be given as:

$$\sum_{t=1}^{t=T} \rho_t \times Day_t + (Wind_t^r - \rho_t) \times Real_t^r, \tag{1}$$

where T is the total number of time periods in the contract and Day_t is the day-ahead market price at time t.

In this fixed contract, windfarm is at risk of incurring a loss if it has a deficit of power and the real-time prices are higher than the day-ahead market price. Windfarm can also miss on opportunities to make extra profit as it could have sold its available power in the real-time market at a (stochastic and unknown) higher price rather than entering into a fixed forward contract at a (known) lower day-ahead price.

2.2 Introduction of flexible forward contract

We introduce a flexible forward contract for the windfarm to trade its power in the day-ahead market. We modify the forward contract in the previous section so that the windfarm can deviate from the committed power supply amount. Suppose the windfarm commits to supply the same amounts of power at time t as in Section 2.1. Instead of the day-ahead market price, this contract is entered at a price of π_t^f per units for interval t. Using the arbitrage free argument,

$$\pi_t^f \leq Day_t. \tag{2}$$

The main parts of the contract are as follows:

1. Windfarm can deviate from the committed amount ρ_t in the contract.
2. Windfarm has to remain within certain bounds of power supply rating at each time interval. This could be different for each time interval.
3. Windfarm must meet certain requirements on cumulative energy it had supplied up to certain pre-specified time intervals.

In the proposed contract, the renewable energy supplier has the ability to supply less than committed power when it experiences a power deficit and it can compensate for this shortfall at a future time interval when it has more energy than it had committed for that time interval. The windfarm can also supply a higher than committed amount of energy if it expects lower generation in the future or expects the real time prices to be higher than the contract price.

The conditions on the contract are listed below:

$$\rho_t^{min} \leq \rho_t^f \leq \rho_t^{max}. \tag{3}$$

Here ρ_t^f is the flexible amount of power that the windfarm can supply and ρ_t^{min} is the minimum amount of power that must be supplied in interval t. This minimum amount could be due to the fixed load at interval t as the windfarm can enter into a contract to supply some fixed load along with some flexible loads. The flexible power is also upper bounded by the windfarm power rating. This would prevent any sort of virtual energy trading by the windfarm.

The other conditions on the cumulative amount of energy are listed below:

$$\sum_{t=n_1}^{n_1+m_1} \rho_t^f \geq E_1 \quad , \quad \sum_{t=n_2}^{n_2+m_2} \rho_t^f \geq E_2 \ldots \sum_{t=n_l}^{n_l+m_l} \rho_t^f \geq E_l, \tag{4}$$

where l is the number of conditions specifying minimum cumulative energy at different time intervals, $n_j \in \{1, 2, \ldots T\}$ is the index for the starting time interval for an energy constraint in the contract and $m_j \in \{0, 1, 2, \ldots T-1\}$ is the total number of time intervals for which the minimum cumulative energy is specified for constraint j. E_j is the minimum total energy that must be supplied by the windfarm from time interval n_j to time interval $n_j + m_j$.

Similarly, the contract can have provisions which would prevent the power supplier from supplying a huge amount of power which may be beyond the flexibility limitations of the load or there may not be enough load to consume such large amount of power or energy.

$$\sum_{t=n_{l+1}}^{n_{l+1}+m_{l+1}} \rho_t^f \leq E_{l+1} \ldots \sum_{t=n_{l+s}}^{n_{l+s}+m_{l+s}} \rho_t^f \leq E_{l+s}. \tag{5}$$

Here s is the number of conditions specifying maximum cumulative energy at different times. $n_j \in \{1, 2, \ldots T\}$ and $m_j \in \{0, 1, 2, \ldots T-1\}$ hold the same meaning as before and E_j is the maximum total energy that the windfarm can provide from time interval n_j to time interval $n_j + m_j$. This prevents the windfarm from supplying a large amount of power which cannot be accepted by the load.

With these conditions for the contract, we can write the payoff function for the windfarm (if it decides to engage in the proposed flexible forward contract) as:

$$\sum_{t=1}^{t=T} \rho_t^f \times \pi_t^f + (Wind_t^r - \rho_t^f) \times Real_t^r. \tag{6}$$

This would provide the payoff for the windfarm in the flexible contract. The flexible power supplied ρ_t^f and contract price π_t^f are subject to the constraints in (2) – (5). Similar to the fixed contract, the windfarm can purchase any shortfall in power from real-time market at the realized real-time electricity price $Real_t^r$. It also has the ability to sell any excess power in the real-time market. However, the flexibility in the contract also provides an advantage to the power supplier by enabling it to sell more power in the real-time market if the real-time prices are higher than the contract price and supplying this power at a later stage when real-time prices are lower than the contract price.

Since there is an obvious advantage for the supplier in such a flexible contract, the load entity can be compensated by a reduction in the transaction price π_t^f. This would depend on a number of factors such as risk of prediction error in load flexibility, forecasting risks in wind and real-time prices, the profit and cost targets for both parties in the contracts, negotiations between supplier and buyer etc.

2.3 Revenue Maximization in flexible contract

The objective of the power supplier in the flexible contract is to maximize the payoff in (6). Since, the actual wind generation $Wind_t^r$ and real-time prices $Real_t^r$ are not known at the time of the contract, this problem becomes a stochastic optimization problem. The objective function changes to maximizing the revenue from (6) using the forecast of wind generation and forecast of real-time price at each time interval. The windfarm objective function becomes,

$$\max_{\rho_t^f} E\left\{\sum_{t=1}^{t=T} \rho_t^f \times \pi_t^f + (Wind_t^f - \rho_t^f) \times Real_t^f\right\}, \tag{7}$$

where $Wind_t^f$ is the forecast of wind generation and $Real_t^f$ is the forecast of real-time price at time interval $t \in \{1, 2 \dots T\}$.

CLAIM:

We claim that the revenue maximization problem of (7) is equivalent to maximizing the following function:

$$\max_{\rho_t^f} \left(\sum_{t=1}^{t=T} \left\{\rho_t^f \left(\pi_t^f - E[Real_t^f]\right)\right\}\right). \tag{8}$$

The proof of this claim is provided in the Appendix A.

This suggests that the strategy adopted by windfarm in the flexible contract proposed here depends only on the real-time prices and does not depend on the forecast of wind power. This may seem unintuitive but the windfarm can make more profit if it sells its power in real-time market when prices in real-time are higher than the contract price and sells the contracted flexible power when real-time prices are lower than the contracted price. Windfarm can do this as long as it meets the conditions on the flexibility in the contract (also given in (3) – (5)). This would result in the maximum expected revenue for the windfarm.

Let ρ_t^{f*} represent the optimal power supply for time t in the flexible contract. Then the expected maximized revenue for the windfarm is:

$$\sum_{t=1}^{t=T} \left\{\rho_t^{f*} \left(\pi_t^f - E[Real_t^f]\right)\right\} + \sum_{t=1}^{t=T} \left\{E\left[Wind_t^f\right] E\left[Real_t^f\right]\right\}. \tag{9}$$

3 Simulation Setup

We want to compare the benefits of the proposed flexible contract against the simple forward contract made in the day-ahead market. For this purpose, we simulate the windfarm operation for both contracts and obtain the revenues achieved by the windfarm in both contracts. We simulate the flexible and forward contracts for a 24 hour period and then repeat this simulation six more times to obtain results for seven consecutive days corresponding to a week.

3.1 Contract duration and time

In the simulation, we assume that the flexible contract starts at 17:00 hrs (5:00 PM) on a day and is entered for the next 24 hours (i.e., from 17:00 Hrs on day 1 to 16:00 Hrs on day 2). The windfarm and the load entity can enter into the contract between 16:00 Hrs and 17:00 Hrs. Therefore all the information (real-time prices, wind generation etc.) up to 16:00 Hrs is known before the contract is agreed upon. Since the day-ahead prices are determined by the ISO in advance, the day-ahead market prices for the next 24 hours are also known to every participant.

3.2 Forecast of wind power and real-time price

We obtain the forecast of the hourly real-time price for seven days beginning at 17:00 Hrs on July-1-2015, using ARIMA modeling techniques. We use the Capital zone of New York Independent System Operator (NYISO) for this purpose [15]. We only forecast the hourly real-time price for the next 24 hours at a time with the first hourly interval for each day beginning at 17:00 Hrs. When we forecast the real-time price for the next day i.e., beginning at 17:00 Hrs on July-2-2015, we already know the realized values of the real-time prices up to 16:00 Hrs on July-2-2015 (which could be different from our previous forecast) and we use that knowledge in our forecast for the next day. Even though we will simulate seven days of a week, price forecast for each day will be a separate forecast and the actual data for the previous day will be known.

Similaly, we select a windfarm from NREL Eastern Wind Integration and Transmission Study (EWITS) [16] located in the same area (i.e., Capital region of New York state). We use ARIMA modeling to forecast the hourly wind power for seven days beginning at 17:00 Hrs on July-1-2006. Similar to the price forecast, we only forecast wind power for the next 24 hours with the first value beginning at 17:00 Hrs. For every set of 24 hours that we forecast, we already know the realized values of the wind power up to 16:00 Hrs on that day (which could be different from our previous forecast) and we use that knowledge in our wind power forecast for the next day.

3.3 Flexible load data

In our simulation, we consider electric cars as the flexible load in the flexible contract. These are ideal for a flexible contract as they possess flexibility in terms of charging duration and the quantity of charge. In our simulation, we consider a base case of 500 electric cars which arrive between 5:00 PM and 9:00 PM for recharging. 20% of the cars arrive at the beginning of every hour from 5:00 PM to 9:00 PM with the first batch of 20% cars (i.e., 100 cars) arriving at 5:00 PM. This is also shown graphically in Figure 1.

Different electric cars available in the market have different battery capacities ranging from 6 kW-hr to 90 kW-hr [17]. We assume an average battery capacity of 50 kW-hr per car. Similarly, there are different type of electric car chargers with different power ratings ranging from 3 kW to 120 kW for vehicle charging [18]. In our simulation, we consider an average power supply rate of 10 kW for each car charger. The power supplier (renewable energy generator) would supply

Table 1: Different parameters of flexible load used in the simulation for base case of 500 cars.

Parameter	Quantity
Number of cars	500
Average capacity of battery per car	50 kW-hr
Average power supply rating per car	10 kW
Average time required to charge a car to its full capacity	5 hours
Flexibility variation in load	0 hours to 9 hours
Cars arriving for charging at beginning of every hour (from 5:00 PM to 9:00 PM)	100
Cars requiring a minimum charging level of 50% of their battery capacity arriving each hour	50
Cars requiring a minimum charging level of 75% of their battery capacity arriving each hour	50

a batch of cars as a combined load at a time, and therefore, we can assume an average power rating and an average battery capacity for this purpose. The information about the simulation setup is also detailed in Table 1.

The cars can also have a different flexibility in the amount of minimum charge that they require. We consider two types of cars:

1. Half of the electric cars require a minimum charging of 50% of their battery capacity.
2. The other half require a minimum charging level of 75% of their battery capacity.

We consider that this flexibility in charging amount is distributed uniformly. Hence, half of the cars arriving at each hour require a minimum charging level of 50% and the other half arriving at that hour require a minimum charging level of 75%. For example, in the base case, 100 cars arrive at 5:00 PM. Therefore, 50 cars arriving at 5:00 PM would be satisfied with a charging level of 50% of their battery capacity (i.e., 25 kW-hr per car) and the other 50 cars require a minimum charging of 75% of their battery capacity (i.e., 37.5 kW-hr per car). This is also shown in Figure 1.

The cars also have a flexibility in their charging duration. In our simulation, a car would take 5 hours to charge completely. Therefore, with no flexibility in duration, an electric car arriving at 08:00 PM must be charged by the windfarm up to atleast the minimum charging requirement in 5 hours (i.e., by 01:00 AM). If the car has a duration flexibility of 4 hours in the charging duration, this provides the power supplier a leniency in the contract and now the requirement is to charge the car to its minimum charging requirement in $5 + 4 = 9$ hours (i.e., by 05:00 AM). This is also illustrated in Figure 2.

In our simulation, we also observe the effect of the flexibility in duration on the windfarm revenues. We vary the flexibility in the charging duration from 0 hours to 9 hours in increments of 1 hour. These results would be described in the next section.

3.4 Contract transaction price

The transaction price of the flexible contract π_t^f in (6) would depend on a number of factors, such as the uncertainty in prediction of load flexibility, accuracy in prediction of real-time prices, targets and objectives of both parties in the contract, etc. Therefore, picking any arbitrary value

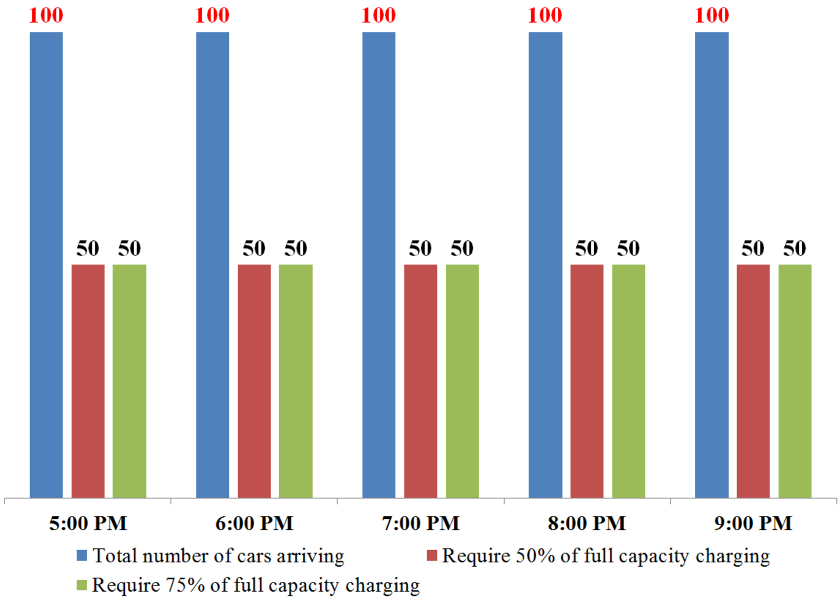

Figure 1: Arrival time of electric cars (flexible loads) and their quantities for the base case of 500 cars.

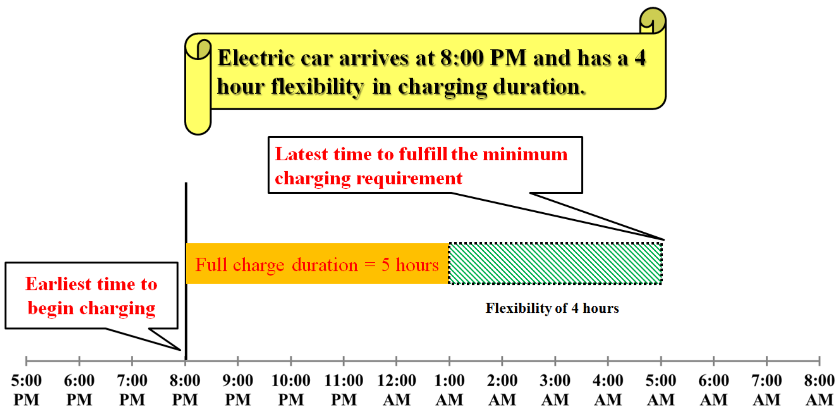

Figure 2: An example of a four hour flexibility in an electric car arriving at 8:00 PM (charging duration is 5 hours, earliest start time is 8:00 PM and latest end time is 05:00 AM).

Table 2: Windfarm revenue in \$/MW of installed capacity, when it enters into a fixed forward contract of 24 hours for seven days (day lasting from 17:00 HRS to 16:00 HRS) in the selected week.

Number of cars	Revenue (\$/MW of windfarm capacity)
400	1,285.93
450	1,278.58
500	1,271.24
550	1,263.90
600	1,256.56

for π_t^f would not be a correct approach. Since, the goal of this research is to show the benefits of the flexible contract over the fixed contract, we decide to use the same value for transaction price in the flexible contract as the value used in the fixed contract (i.e., day-ahead market price). In our simulation and results, we have:

$$\pi_t^f = Day_t. \tag{10}$$

By using the day-ahead price as the transaction price, we can get an accurate value for the increase in windfarm revenues if it switched to a flexible contract instead of a fixed contract entered in the day-ahead market. This increase in revenue can be taken into account when the buyer and supplier settle on a negotiated transaction price for the flexible contract.

4 Results and Discussion

We now present and explain the results of our simulations. We consider two cases in our simulation and analysis. These will be described now.

4.1 Case 1: (A fixed forward contract)

First we consider the simple case of a fixed forward contract. Here the windfarm commits to supply a fixed quantity of load at a fixed price (which is the day-ahead market price) for each interval. We consider a set of 500 cars as our base case as mentioned in the previous section. The arrival time of cars and their quantities at each hour are same as described in the simulation setup and Figure 1 in Section 3. We change the number of cars from 400 to 600 in increments of 50 cars and calculate the revenue of windfarm for each quantity of cars. In our calculation, the payoff for the windfarm is calculated in the same way as (1). Once all the cars are charged (i.e., after 2:00 AM), then the windfarm sells its power in real-time market for the rest of the 24 hour period (i.e., until 5:00 PM). The results are provided in Table 2.

Interestingly, the windfarm revenue shows a declining trend as the amount of fixed load is increased. This is because of the fact that the windfarm does not have sufficient wind power available at certain times when it needs to supply the load and it has to buy that shortfall from real-time market. If the real-time prices are higher than the day-ahead prices at those time intervals (when windfarm has a deficit of power), then windfarm would incur a loss. This effect would be less significant and may not even happen when the contracted fixed load is low (e.g., 400 cars vs 600 cars).

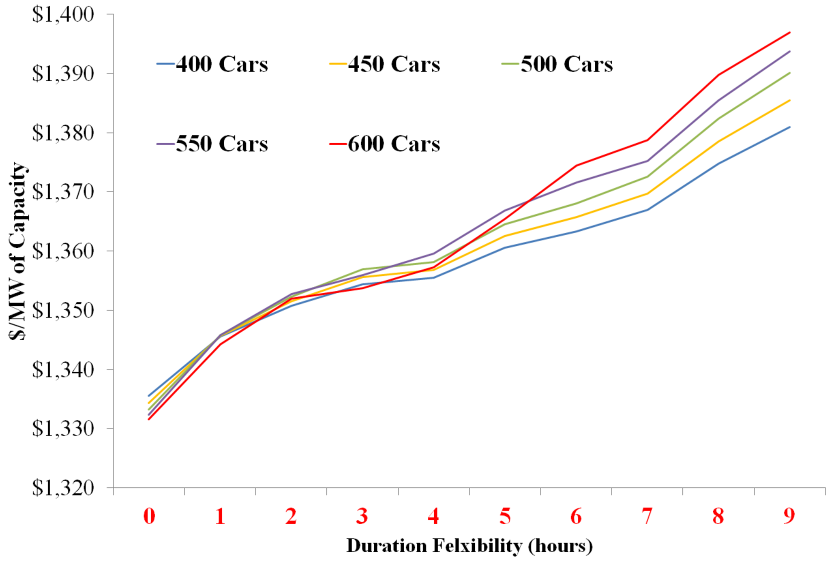

Figure 3: Graphical representation of windfarm revenues against different levels of flexibility in load when forecast of real-time price is used in (8).

4.2 Case 2: (Flexible contract with only flexible loads)

In Case 2, we utilize the flexible forward contract described in Section 2. In this case, the windfarm enters into a flexible contract with only flexible loads and does not supply any amount of fixed load. A set of 500 cars is our base case like before and the arrival time of cars and their quantities at each hour are same as described in Section 3. We again change the number of cars from 400 to 600 in increments of 50 cars. The transaction price has the same value as one given in (10).

We also observe the effects of increase in the flexibility (in terms of duration) on the revenue of power supplier. We vary the flexibility in load duration from 0 hour (no flexibility in time) to 9 hours. The windfarm optimizes its payoff function of the flexible contract as described in (8), while satisfying all the constraints and remaining within the appropriate limits of flexibility at every time interval. We run this simulation twice using two different sets of real-time price in (8) for maximization of payoff from flexible contracts.

First we consider the forecast value of real-time price obtained using the ARIMA forecasting techniques. Then we use the actual value of real-time price. In the latter case we consider that the power supplier possesses the perfect knowledge about the real-time prices for the next 24 hours. We do this to observe the effect of the accuracy in price forecast on the overall results.

We use the forecast of real-time price in (8) and optimize the operation of windfarm to maximize its payoff. These results are shown in Table 3. The values represent the revenue of power supplier in $/MW of nameplate capacity if it enters into the flexible contract of 24 hours for seven days in the selected week. The results from Table 3 are also shown in Figure 3 graphically.

The obvious observation is that the revenue per unit of windfarm capacity increases as we increase the amount of flexibility in the load. This was expected as more flexibility allows the windfarm to sell its power to the flexible load when real-time prices are lower than the day-ahead prices. It also allows the windfarm an advantage to sell more power in real-time than it would have (if flexibility was low) when real-time prices are higher. We also note that for higher

Table 3: Windfarm revenue in \$/MW of installed capacity for different levels of flexibility calculated using forecast of real-time prices, when it enters into a flexible forward contract of 24 hours for seven days in the selected week.

Flexibility in duration	Number of Cars				
(hours)	400	450	500	550	600
0	1,336	1,334	1,333	1,332	1,332
1	1,346	1,346	1,346	1,346	1,344
2	1,351	1,352	1,352	1,353	1,352
3	1,354	1,356	1,357	1,356	1,354
4	1,355	1,357	1,358	1,360	1,357
5	1,361	1,363	1,365	1,367	1,365
6	1,363	1,366	1,368	1,372	1,374
7	1,367	1,370	1,373	1,375	1,379
8	1,375	1,379	1,382	1,385	1,390
9	1,381	1,386	1,390	1,394	1,397

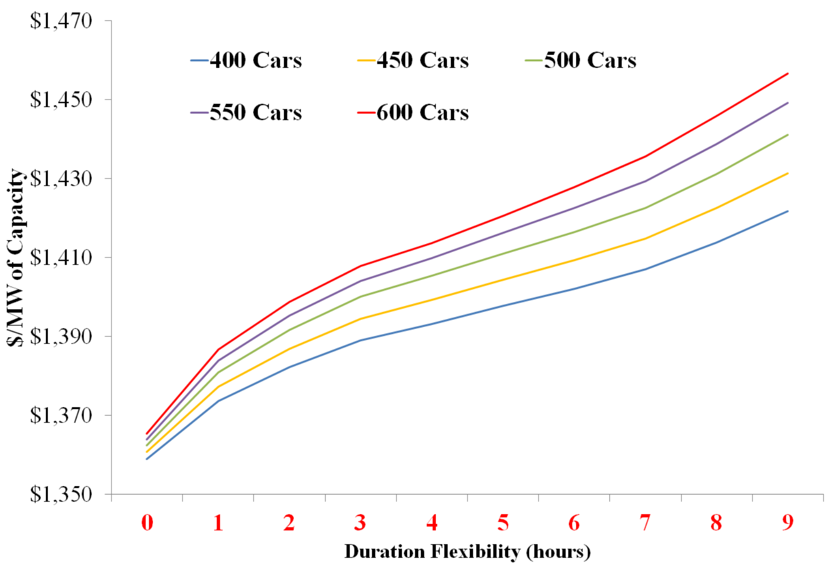

Figure 4: Graphical representation of windfarm revenues against different levels of flexibility in load when actual value of real-time price is used in (8).

Table 4: Windfarm revenue in \$/MW of installed capacity for different levels of flexibility calculated using actual value of real-time prices, when it enters into a flexible forward contract of 24 hours for seven days in the selected week.

Flexibility in duration (hours)	Number of Cars				
	400	450	500	550	600
0	1,359	1,361	1,362	1,364	1,365
1	1,374	1,377	1,381	1,384	1,387
2	1,382	1,387	1,392	1,395	1,399
3	1,389	1,395	1,400	1,404	1,408
4	1,393	1,399	1,405	1,410	1,414
5	1,398	1,404	1,411	1,416	1,421
6	1,402	1,409	1,417	1,423	1,428
7	1,407	1,415	1,423	1,429	1,436
8	1,414	1,423	1,431	1,439	1,446
9	1,422	1,431	1,441	1,449	1,457

levels of flexibility, the windfarm earns more revenue for supplying a higher quantity of load than it does for supplying a lower amount of load. This is different from the values in Table 2 for a fixed forward contract. This is because a larger flexibility in load prevents the windfarm from purchasing the power in real-time market at a higher price to fulfill its obligation in case it has a shortfall. Windfarm can simply move its supply to a different hour with relatively lower real-time price and purchase the deficit at a lower price.

Now we use the actual value of real-time price in (8) and optimize the operation of windfarm to maximize its payoff. Here, we are assuming perfect knowledge of future prices. These results are shown in Table 4 and Figure 4. As expected, the power supplier makes more revenue per unit of capacity if the forecast is accurate. A comparison of Table 3 and Table 4 shows that for every quantity of load and flexibility, the revenue is higher when forecast is perfect. Figure 4 also shows a consistent increase in revenue with increase in amount of load and flexibility as compared to Figure 3.

In order to show, how windfarm operation is affected by different values of flexibility, we plot the power supplied at the 24 hourly intervals of day 2 for three different flexibility values (3 hour, 6 hour and 9 hour) in Figure 5. The supplied power in Figure 5 is calculated by using the perfect forecast of real-time price in (8) for the base case of 500 cars. We can see how the increase in flexibility allows the power supplier to distribute its supply over a longer time horizon. For a flexibility of 9 hours, the supplier can also supply power at 9:00 AM and 10:00 AM which would not happen for the other two values of flexibility in load.

4.3 Benefit to flexible load

Under the proposed contracting mechanism, it may appear that the windfarm would try to supply the load in hours with higher day-ahead prices but this is because we assumed the contract transaction price to be equal to the day-ahead market price for the purpose of finding out the benefits to the renewable energy supplier. In reality, the transaction price for each time interval in the proposed flexible forward contract will be lower than the day-ahead market price. This price would be negotiated between the supplier and buyer based on a number of factors

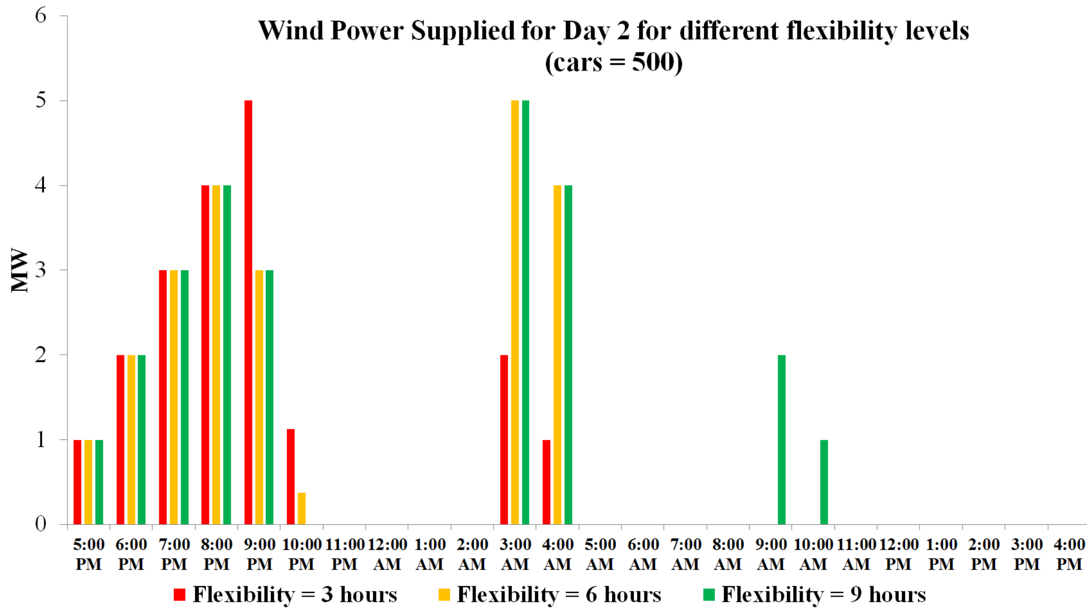

Figure 5: A comparison of supplied power to a flexible load of 500 cars on day 2 for three different values of load flexibility in Case 2.

such as accuracy in prediction of load flexibility, accuracy in real time price forecast etc.

Here, we provide an example of a transaction price for the proposed flexible contract. Since, there is a flexibility in the forward contract and an obvious benefit for the power supplier, therefore the transaction price of the proposed contract should be lower than that of a simple fixed forward contract (i.e., lower than the day-ahead price). Table 5 shows the day-ahead price and an assumed transaction price for the flexible forward contract negotiated between the supplier and flexible load for day 1 in the selected week.

We are considering the case with 3 hours of flexibility in the charging duration. For the sake of simplicity, we consider that all cars need to be charged to 100% of their battery capacity. For the sake of simplicity, we also assume that the entity controlling the flexible load is completely aware of the amount of flexibility in the load and it does not have any prediction error in arrival times and duration flexibility of the arriving cars. If we do not make this assumption, then coming up with an arbitrary value of negotiated transaction price shown in Table 5 would be difficult as we would need to account for the prediction error in load flexibility.

The load would prefer to be supplied in the hours with the lowest day-ahead prices within the flexibility interval. With 3 hours of flexibility, these are hours from 20:00 Hrs to 04:00 Hrs. Therefore, there is no incentive for the load to agree to a transaction price above 16.3 \$/MWhr in any time interval other than 20:00 Hrs to 04:00 Hrs. Using the example of negotiated transaction price in Table 5, we calculate the revenue of the windfarm with the proposed flexible contracting mechanism. These values are shown in Table 6. Table 6 also shows that the windfarm revenue from the proposed flexible contract is greater than the windfarm revenue if it were to only sell in real time markets. Similarly, the reduced transaction price also leads to lower costs for flexible loads as shown in Table 6.

Table 5: An example of negotiated transaction price in the proposed flexible contract for a flexibility of 3 hours in day 1 in the selected week.

Time (Hrs)	Power supplied (MW)	Day-ahead price ($\$/MWhr$)	Transaction price ($\$/MWhr$)
17:00	0	52.6	16.0
18:00	0	48.4	16.0
19:00	0	41.3	16.0
20:00	1	36.9	36.4
21:00	2	29.3	28.8
22:00	3	28.5	28.0
23:00	4	27.0	26.5
00:00	5	25.3	24.8
01:00	4	20.1	19.6
02:00	3	16.6	16.1
03:00	2	16.3	15.8
04:00	1	17.1	16.6

Table 6: Windfarm revenues and payments made by load under different contracts for a flexibility of 3 hours in day 1 in the selected week.

Revenues and Payments	Amount ($)
Payments by load in day-ahead market	595.64
Payments by load in proposed contract	583.14
Windfarm revenue if it sells in real time	282.98
Windfarm revenue in proposed contract	464.33

5 Conclusion

We presented a new form of contracting scheme for renewable energy generators with intermittent generation issues. Our proposed contracting mechanism allows the renewable power supplier to enter into a contract with flexible loads and take advantage of this flexibility by changing their power dispatch from the committed amounts. If the generation is less than the expected or committed amount in the contract, the supplier can change its power dispatch as long as it satisfies the conditions on cumulative energy up to different time intervals and remains within the limits of flexibility.

Such a contract also allows the renewable energy supplier to sell its power in real time market when real time prices are high. So, if the real time prices are higher than the transaction price in the contract and the flexibility in the contract allows the supplier to postpone its committed power supply, it can sell its available energy in real time market at higher prices. This type of scheme provides additional benefits to the power supplier. As a result, the transaction price of such a contract could be made less than the day-ahead market price and this would benefit the consumer as well because they would be paying less than the day-ahead market price in this situation.

We considered electric cars as the flexible load in the flexible contract and used a windfarm from NREL EWITS located in the Capital region of New York state. We used the day-ahead and real time price data from the same region and used same time of the year (as wind generation data) and simulated our flexible contract. We varied the flexibility in charging duration from 0 hour to 9 hours and also changed the number of cars. Our results show that the increase in flexibility increases the revenue per unit of installed capacity of renewable generation. We also notice that the accuracy in forecast of real time prices increases the payoff for the power supplier. Therefore, we can conclude that a greater degree of flexibility in the load leads to larger benefits for the renewable generators.

In this research, we assumed that the renewable energy supplier has information about all the loads (flexible and fixed) in the contract. However, it may happen that the power supplier will make the contract with an aggregator or a utility which supplies a mixture of fixed and flexible loads. In this case, the supplier may not be aware of all the information regarding the loads and the aggregator has to aggregate all the loads in such a way that the information regarding the flexibility and other load characteristics is not compromised. This can be achieved by using aggregation algorithms that combine the fixed and flexible loads at different time intervals and provide a single load profile with lower and upper limits to include the flexibility in the load. The renewable energy supplier will then work with this aggregated load profile and optimize its payoff within the flexibility limits. Developing these aggregation algorithms and using them in the flexible contracts is an interesting topic for future research.

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A

From (7), we have

$$\max_{\rho_t^f} E\left\{\sum_{t=1}^{t=T}\left[\rho_t^f\left(\pi_t^f - Real_t^f\right) + Wind_t^f \times Real_t^f\right]\right\}. \tag{A.1}$$

$$\max_{\rho_t^f}\left(E\left\{\sum_{t=1}^{t=T}\left[\rho_t^f\left(\pi_t^f - Real_t^f\right)\right]\right\} + E\left\{\sum_{t=1}^{t=T}\left[Wind_t^f \times Real_t^f\right]\right\}\right). \tag{A.2}$$

$$\max_{\rho_t^f}\left(\sum_{t=1}^{t=T} E\left[\rho_t^f\left(\pi_t^f - Real_t^f\right)\right] + \sum_{t=1}^{t=T} E\left[Wind_t^f \times Real_t^f\right]\right). \tag{A.3}$$

As we assumed in Section 2.1 that the amount of wind energy in the system is small enough that the wind generation does not have an effect on the electricity prices. Moreover, it is trivial that the real-time prices do not affect wind speed or wind generation since wind speed is a process independent of market price. This assumed independence between real-time prices and wind generation implies that the two variables are uncorrelated.

$$Corr(Wind_t^f, Real_t^f) = 0. \tag{A.4}$$

Therfore:

$$E\left[Wind_t^f \times Real_t^f\right] = E\left[Wind_t^f\right] \times E\left[Real_t^f\right]. \tag{A.5}$$

So(A.3) becomes

$$\max_{\rho_t^f}\left(\sum_{t=1}^{t=T}\left\{E\left[\rho_t^f\pi_t^f\right]-E\left[\rho_t^f Real_t^f\right]\right\}+\sum_{t=1}^{t=T}\left\{E\left[Wind_t^f\right]\times E\left[Real_t^f\right]\right\}\right). \tag{A.6}$$

Now, ρ_t^f and π_t^f are constant terms. Therefore:

$$E\left[\rho_t^f\pi_t^f\right]=\rho_t^f\pi_t^f \quad , \quad E\left[\rho_t^f Real_t^f\right]=\rho_t^f\, E\left[Real_t^f\right]. \tag{A.7}$$

(A.6) becomes

$$\max_{\rho_t^f}\left(\sum_{t=1}^{t=T}\left\{\rho_t^f\left(\pi_t^f-E[Real_t^f]\right)\right\}+Z\right), \tag{A.8}$$

where $Z=\sum_{t=1}^{t=T}\left\{E\left[Wind_t^f\right]\times E\left[Real_t^f\right]\right\}$ is a constant term. This reduces the revenue maximization problem to:

$$\max_{\rho_t^f}\left(\sum_{t=1}^{t=T}\left\{\rho_t^f\left(\pi_t^f-E[Real_t^f]\right)\right\}+Z\right)\equiv\max_{\rho_t^f}\left(\sum_{t=1}^{t=T}\left\{\rho_t^f\left(\pi_t^f-E[Real_t^f]\right)\right\}\right), \tag{A.9}$$

which is the same as our claim in (8).