Economic Valuation of Wind Curtailment Rights

N. P. Yu, *Member, IEEE*, H. Y. Sheng, and R. Johnson, *Member, IEEE*

Abstract—**The proportion of wind capacity in the generation portfolio continues to expand with increasing renewable penetration in the United States. The combination of more frequent negative real-time locational marginal prices and over-generation from wind farms has started to reduce wind farm owners' operating profit in Independent System Operator (ISO) managed electricity markets. Therefore, it is vital for utilities/independent power producer to start negotiating (or renegotiating) wind energy procurement contracts with developers to include some type of curtailment rights. The contract negotiations call for the development of a comprehensive methodology to conduct economic valuation on curtailment rights. This paper addresses the needs by proposing a new method for evaluating wind farm curtailment rights. The valuation methodology not only considers the financial aspect but also closely models the physical dispatch of wind farms. The valuation method is applied to a generic wind farm in the California ISO (CAISO) system. The simulation results demonstrate that curtailment rights have a significant value to wind farm owners if the resource is bid appropriately into the wholesale power market.**

Index Terms—**Wind Curtailment, Markov Regime Switching, Wholesale Power Market, Contract Valuation.**

I. Introduction

In the United States, the wind capacity as a percentage of the total generation capacity increased from 1.1% in 2006 to 3.6% in 2010 [1]. At the same time, wind capacity as a percentage of the entire generation portfolio capacity in each ISO managed market also continues to increase. Electric Reliability Council of Texas (ERCOT), Midwest Independent System Operator (MISO) and CAISO are the top three ISO managed markets with the highest level of wind penetration. At the end of 2011, the wind capacity as a percentage of entire generation portfolio is about 11.4% in ERCOT [2], 8.1% in MISO [3] and 7.6% in CAISO [4].

Two major challenges associated with the integration of wind resources into the U.S. electric system are identified in the report titled “20% Wind Energy by 2030” [5]. The first challenge arises from the intermittent nature of wind power and the “non-dispatchability” of wind resources in electric power market operations. As estimated in various studies, with 20% wind penetration, the system operating cost incurred due to variability and uncertainty of wind power is about 10% of the wholesale value of the wind energy [5].

To reduce the cost of integrating wind resources into electric systems, the industry has been tackling both the intermittency and “non-dispatchability” issues related to wind. The intermittency of wind power is being addressed by improving wind forecasting performance, by dispersing farm developments geographically to reduce concentrated variability, and by virtual/physical consolidation of balancing areas.

Electric market operators in the U.S. are also working with market participants to better utilize the limited dispatchability of wind turbines. Until recently, wind farms have been deemed non-dispatchable in electric power market operations. However, with research and development advancement in wind technology, modern wind turbines have a ramping capability of up to 10 percent of turbine rating per minute [6].

Initially when wind farms participated in the ISO organized markets, the power from wind farms was self-scheduled into the Real-Time (RT) market and the energy is treated as "must take". With increased wind penetration, the frequency of negative locational marginal price (LMP) at the wind farm’s pricing nodes is increasing dramatically. The negative prices indicate that the RT market had to dispatch negatively priced offers to meet demand. Occasionally, the energy component of the LMPs have been even lower than the bid floor (e.g. $-30/MWh in CAISO) which means there was not enough dispatchable downward capacity to meet the imbalance requirement during the dispatch interval. Although the wind farm receives negative payment to generate power, some of them are not willing to curtail output due to other considerations such as production tax credits, and renewable energy credits (RECs).

As wind penetration reaches a certain levels, the RT market mechanism itself is not able to handle the intermittency of wind. Frequent manual wind curtailments are needed to manage congestion and maintain system reliability. To cope with this excessive manual curtailment of wind, MISO and ERCOT started implementing programs that utilize the limited dispatchability of intermittent resources. These programs use forecasted maximum output of wind resources to dispatch them down or back up in real-time based on the resource level offer and system conditions. Some significant benefits have been achieved such as improved congestion management, increased market efficiency, reduced the system regulation service burden and enhanced overall system control

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performance [7].

With the production tax credit for wind projects put on hold for 2013, it is crucial for utilities/independent power producer to start negotiating (or renegotiating) wind energy procurement contracts with developers to include some type of curtailment rights. There are several types of curtailment rights in the industry. This paper studies one the most popular type, take or pay curtailment rights. This type of curtailment rights will allow wind scheduling parties to significantly reduce their risk and cost associated with negative RT prices and over-generation without hurting the wind farm developer. The limited dispatchability from wind generators will improve system reliability, reduce burden on ancillary services and enhance market efficiency. However, the subject of economic values of curtailment rights for wind generation has not been fully investigated. This research fills this gap in power economics by providing a practical economic valuation of wind curtailment rights from utility and independent power producer's perspectives to facilitate the contract negotiation process. The valuation methodology is based on both economic theory and the practice of electricity market operations.

The remaining of this paper is structured as follows. Section II presents the problem formulation and technical method used in the economic valuation of wind curtailment rights. Section III provides the case study results. The conclusions are stated in Section IV.

II. Problem Formulation and Technical Method

This section is concerned with the problem formulation of economic valuation of wind farm curtailment rights and the valuation techniques. The general idea for valuing the curtailment right is to calculate the difference between wind farm revenues with and without curtailment rights. Since day-ahead market LMP rarely drops below zero, it is assumed that wind curtailment occurs mostly in the real-time market. The value of curtailment rigths can be represented as

$$\pi_{Curtail} = \sum_{t=1}^{T} e^{-rt}[(P_t - P_t^{wc}) \times RT\ LMP_t] \qquad (1)$$

where $\pi_{Curtail}$ stands for value of economic curtailment right, t denotes for interval t, r denotes the discount rate, P_t^{wc} denotes wind production in interval t without curtailment right. The symbol P_t denotes wind production in interval t with curtailment right and $RT\ LMP_t$ is the RT LMP for interval t.

The valuation process is structured as follows. First, the stochastic processes for RT LMPs and wind farm capacity factors are built. Second, Monte Carlo simulation is conducted to produce samples of the RT LMPs and wind farm production. Afterwards, the wind farm dispatches are simulated based on RT LMPs and various energy bid curve structure assumptions. Finally, the NPV of wind farm curtailment rights are calculated by summing up the discounted differences between wind farm revenue with and without curtailment rights.

A. RT LMPs Model

Since in ISO/RTO markets power plants are usually dispatched on a 5 minute interval basis and RT market usually runs at the granularity of 5 minutes, the RT LMPs need to be modeled on a 5 minute interval basis for wind farm curtailment rights valuation.

In the literature, there are numerous reports on the study of forward power prices, day-ahead LMPs because most of the power plants' revenues come from long-term forward contracts and/or day-ahead market. To study the unique properties of forward power prices and DA LMPs, researchers have proposed various modeling approaches that modified and extended the traditional time series models. These models include Autoregressive Integrated Moving Average (ARIMA) and its variants [8,9], Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and its variants [10], dynamic regression models [11], transfer function models [12], Markov regime-switching models [13,14], mean-reversion models [15,16], and jump-diffusion model [17-19].

Compared to DA LMPs, RT LMPs usually exhibit much higher volatility and frequency of spikes. This is mainly due to the fact that RT market is much closer to actual delivery of electricity than DA market. The longer look-ahead horizon gives DA market the flexibility to deal with expected generation, transmission outage and variability in renewable generation and load. However, if there is a generation outage right before the RT economic dispatch in the RT market, there could be a temporary real power shortage, making the real power balance constraint binding for a few intervals. This most likely creates positive price spikes for a few intervals which will only be limited by the administrative price set by the system operator. Similarly, a gust of wind which increases wind farm output for a few minutes could create real power surplus. If there are not enough downward ramping capabilities in the system, negative price spikes could persist for a few intervals.

Instead of modeling RT LMPs directly, the difference between RT and DA LMPs which is called DART spread is modeled. The idea is that DA LMPs are much easier to forecast given the existence of forward price quotes. Due to convergence bidding, the RT LMPs should converge in the long run to DA LMPs. Since, the DART spread converges to zero in the long run, it is much more stable and less dependent on the high level market drivers such as fuel price, technology advancement, seasonality and changes in the regulatory environment. The forecasted RT price will be derived by summing up the Monte-Carlo simulation of DART spread and DA LMPs.

The extremely high volatility and spikiness of DART spread makes Markov regime-switching model (MRS) a logical candidate for modeling. To the best of the authors' knowledge, this research is the first to apply MRS models to study RT LMPs. Several different model specifications are proposed and tested here.

Suppose that the DART spread time series has a sample size of T. It is assumed that the $y_t = \log(DART_t + const_1) + const_2$ may occasionally shift between K possible regimes/states from which a particular sample y_t is drawn. The unobservable regimes/states at time t is denoted by s_t which can take on an integer value in {1,…,K}. It is further postulated that the transition between states is governed by a Markov chain whose realizations take on values in {1,…,K}. The transition matrix P contains the probabilities $p_{ij} = P(S_{t+1} = j|S_t = i)$ of switching from regime i at time t to regime j at time t+1.

Based on MRS models fitted for Day-Ahead and forward prices and the unique characteristics of the DART spread [20], five model specifications are proposed and tested in this research. The detailed specifications are listed in Table I.

TABLE I
MARKOV REGIME SWITCHING MODEL SPECIFICATIONS

Model	Number of States	Base Regime	Spike Regime(s)
1	2	Normal Distribution	Normal Distribution
2	2	AR(1)	AR(1)
3	3	Normal Distribution	Normal Distribution
4	3	AR(1)	Normal Distribution
5	3	AR(1)	Truncated Log Normal Distribution

The estimation of distribution parameters $\boldsymbol{\theta}$, Markov transition probabilities $\boldsymbol{p}$ and initial state probability distributions $\boldsymbol{\rho}$ follows the Expectation-Maximization (EM) algorithm introduced by Hamilton [21] and refined by Kim [22] for MRS models. The parameter vector $\boldsymbol{\lambda}$ is defined as $(\boldsymbol{\theta}, \boldsymbol{p}, \boldsymbol{\rho})$.

The detailed model calibration method is described here. The algorithm starts with an arbitrary guess for the parameter vector $\boldsymbol{\lambda_0}$. In the first step (E-step), the smoothed probabilities $p(s_t, \dots, s_{t-m}|\boldsymbol{y}; \boldsymbol{\lambda_0})$ are calculated based on the initial guess, where $\boldsymbol{y} = (\boldsymbol{y_T}, \dots, \boldsymbol{y_1})$ and m stands for the maximal autoregressive lag order of the regime distributions. Next, in the second step (M-step), maximum likelihood estimates of the distribution parameters and initial state probability distributions are calculated based on equations (2-4). The two steps are repeated until convergence criteria are satisfied.

$$p_{ij}^{(l+1)} = \frac{\sum_{t=m+1}^{T} p(s_t=j, s_{t-1}=i|y;\lambda_l)}{\sum_{t=m+1}^{T} p(s_{t-1}=i|y;\lambda_l)}, \; i,j = 1, \dots, K \quad (2)$$

$$\sum_{t=m+1}^{T} \sum_{s_t=1}^{K} \cdots \sum_{s_{t-m}=1}^{K} \frac{\partial \log p(y_t|z_t;\theta)}{\partial \theta} |_{\theta=\theta_{l+1}} \cdot p(s_t, \dots, s_{t-m}|\boldsymbol{y}; \lambda_l) = 0 \quad (3)$$

$$\rho_{i_m, i_{m-1}, \dots, i_1}^{(l+1)} = p(s_m = i_m, s_m = i_{m-1}, \dots, s_1 = i_1|\boldsymbol{y}; \lambda_l) \quad (4)$$

B. Wind Farm Output Model

The methodology for simulating/modeling wind capacity factor or wind farm outputs could be separated into two approaches [23]. In the first approach, wind speed is simulated and fed into a wind farm model which produces simulated wind output from the wind farm. In the second approach, the wind farm output time series is modeled and simulated directly. Since historical measurements of the wind speed are not always available, this research adopts the second approach to model and simulate the wind farm capacity factor directly. Many statistical methods have been used to model wind farm capacity factor/outputs. These methods include autoregressive moving average (ARMA) model [23-25], limited autoregressive integrated moving average (ARIMA) model [23], and Markov regime switching model [26]. Although ARMA and ARIMA model can reasonably approximate the sample autocorrelation and partial autocorrelation and conduct short-term forecast, they are not very useful in long-term wind farm output modeling. Similarly, short-term forecasting rather than modeling capability of MRS model has been demonstrated in the literature [26]. The goal of this research is to quantify the value of long-term wind farm curtailment rights. Therefore, historical sampling method is used to model the wind farm output series. The advantage of the historical sampling methodology is that the output series not only captures the historical seasonal, diurnal variations but also closely emulates the historical wind output autocorrelations and volatilities.

C. Wind Farm Dispatch Simulation

The wind farm dispatch depends heavily on the energy bids that the wind farm submits to the RT market. Assume that the wind farm's RT energy bid curve has a structure shown in Figure 2.

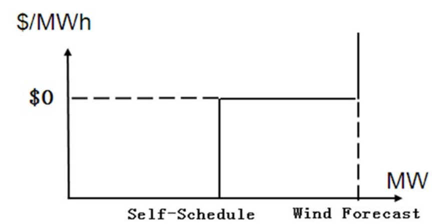

Fig. 2. Wind Farm RT Energy Bid Curve Structure

The RT energy bid curve has a self-schedule portion and one economic bid step. The economic bid step allows the unit to be dispatched at full potential when the RT LMP is nonnegative. The self-schedule portion prohibits the wind farm to operate lower than a certain limit when the RT LMP is negative. The ramping rate submitted together with the energy bid curve is 10% of potential output per minute. It is assumed that self-schedule quantity is the decision variable that wind farm controls. In this research, the self-schedule quantity as a percentage of wind forecast is considered a treatment factor. The curtailment right will be valued for different levels of the self-schedule.

The 5-min RT market clearing mechanism is similar to the one shown in [27]. The only difference for wind farm dispatch is that the ramping rate is a percentage of the farm's potential output. An example of the 5-min RT market clearing results and RT LMPs are shown in Figure 3.

In this example, it is assumed that the potential wind production level for the full hour is 100 MW and the self-schedule level of the wind farm is 25 MW. Assume that the operating hour is HE 14. The RT economic dispatch run results for interval from 13:10 to 13:15 are produced at 13:05. The wind farm is supposed to ramp start from 13:07:30 to reach 100 MW at 13:12:30. The wind farm's ramping rate is 10 MW/min which equals to 10% of wind farm's potential output per minute. When the RT LMP for interval from 13:15 to 13:20 drops below zero, the wind farm should receive a dispatch to start ramping down at 13:12:30 to 50 MW at 13:17:30. Since, the farm self-schedules at 25 MW, the dispatch operating point for interval from 13:20 to 13:25 does not go below 25 MW.

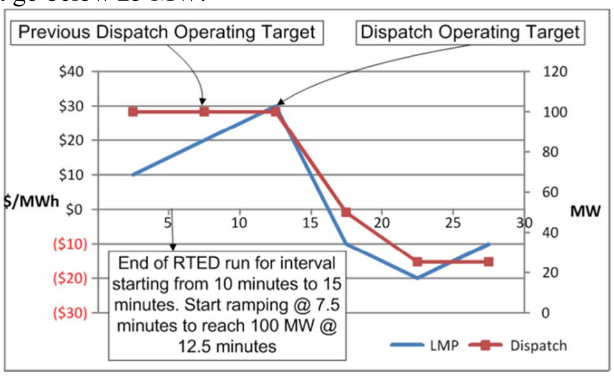

Fig. 3. 5-min RT Market Clearing Results Example

III. Case Study

The economic valuation of wind curtailment rights is conducted for a generic wind farm with a nameplate capacity of 1000 MW located in CAISO. The LMPs data is CAISO's Antelope PNode from Aug 1st 2011 to July 31st 2012 and BPA wind generation capacity factor data from 2009 to 2011.

TABLE II
Key Descriptive Statistics of Fitted MRS Models

Model	1	2	3	4	5	Raw Data
IQR	12.2	37.7	14.3	36.4	12.2	13.4
IDR	27.6	72.6	25.5	70.7	31.3	27.4
Mean	-3.3	-1.1	-3.2	-0.4	-1.9	-2.1
Median	-3.7	-5.2	-3.5	-3.8	-4.5	-4.0
Std	21.5	29.5	23.9	28.6	28.8	51.7
Skewness	3.0	0.9	5.5	0.8	10.9	15.8
Kurtosis	33.6	4.5	76.4	4.2	226.9	282.0
LogL	18842	45233	26453	44914	48214	

Following the valuation process presented in Section II, the stochastic processes for RT LMPs are established first. The five models proposed in Section II.A are fitted to the CAISO's Antelope nodal DART spread. The goodness-of-fit of the models are measured based on the Log likelihood value of each model and the key descriptive statistics. The descriptive statistics includes the Inter-Quartile and Inter-Decile range, mean, median, standard deviation, skewness and kurtosis of the simulated DART spread process. The key descriptive statistics and the Log Likelihood for each model are presented in Table II. The descriptive statistics are obtained from 100 simulated sample trajectories of each model. As shown in Table II, Model 5 has the highest level of Log Likelihood. Moreover, the key descriptive statistics of model 5 are the closest to that of the raw data. Therefore, Model 5 is selected to model the DART spread on 5-min interval basis.

Due to space limit, the fitted model parameters are not shown in this paper. The detailed model fitting results can be found in [28]. The wind farm capacity factors are modeled and simulated using historical sampling method as explained in Section II.B. The sample size for simulated RT LMPs and simulated wind capacity factors are both 100.

The wind farm is then dispatched based on sample RT LMPs, wind capacity factors and RT bid curve assumptions in Section II.C. Finally, the curtailment right value is measured as the sum of the discounted differences between the hourly revenue of the wind farm when it has curtailment rights and the revenue when it does not have curtailment rights.

The mean and standard deviation of curtailment rights value for this wind farm in a year under different levels of self-schedule quantities are given in Table III.

TABLE III
Expected Value and Standard Deviation of Curtailment Right Net Present Value

Self-Schedule as a Percentage of Potential Output	Expected Net Present Value of Curtailment Right	Standard Deviation of Curtailment Right Net Present Value
0%	$1.38 Million	$0.17 Million
25%	$1.07 Million	$0.13 Million
50%	$0.77 Million	$0.09 Million
75%	$0.39 Million	$0.04 Million

As shown in Table III, the expected value and standard deviation of the curtailment right value increases with the decrease of self-schedule level. In other words, by giving the wind farm more flexibility to ramp up and down, the curtailment rights value significantly increases. It should also be noted that the magnitude of the expected curtailment rights value is significant. In addition, the variability of curtailment rights value is relatively small compared with its expected value. The low uncertainty associated with the curtailment right value should facilitate the curtailment right negotiation between wind farm developers and utilities/independent power producers.

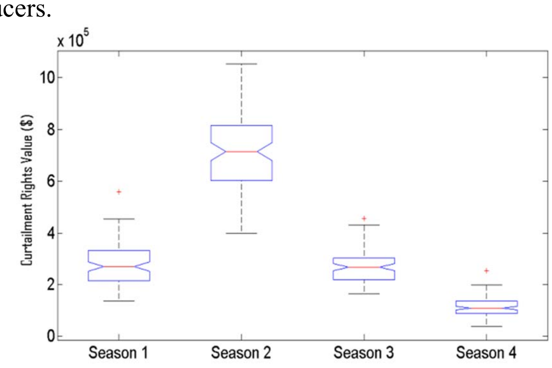

Fig. 4. Box Plot for Seasonal Curtailment Rights Value

The box plot for seasonal curtailment rights value is shown in Figure. 4. As expected the Spring period (April - June) has the highest expected curtailment right value and variability due to higher wind capacity factor and lower RT LMPs. On the contrary, the 4th quarter of the year (October - December) has the lowest expected curtailment right value and variability.

Similarly the hourly curtailment rights value also has a certain pattern as depicted in Figure 5. The curtailment right generally has a higher value during early morning hours when the average wind farm capacity factors are higher and RT LMPs are softer. The curtailment right has a lower value during the day time when wind farm capacity factors are lower and RT LMPs are stronger.

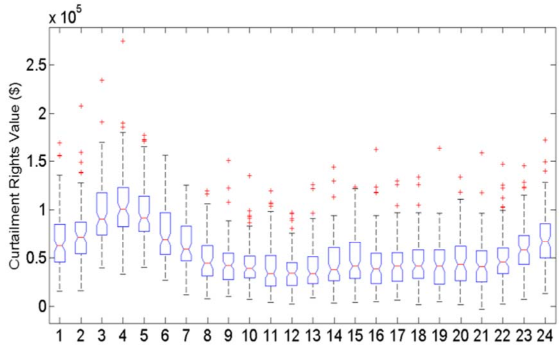

Fig. 5. Box Plot for Hourly Curtailment Rights Value

IV. Conclusion

This paper presents a comprehensive framework to conduct economic valuation of wind farm curtailment rights. The valuation model serves as a useful tool in the curtailment contract valuation and negotiation process. It is shown that the 3-state MRS model with order 1 autoregressive model as base regime and lognormal distribution as spike regimes is well suited to model risks associated with RT LMP. The significant value of wind curtailment rights during early morning hours of spring period are demonstrated by the case study results. The simulation results also show that the curtailment rights value significantly increases with a higher level of operational flexibility as reflected in the bid curve.

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VI. Biographies

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