Strategic Selection of Capacity and Mileage Bids in California ISO Performance-based Regulation Market

Ashkan Sadeghi-Mobarakeh and Hamed Mohsenian-Rad
Department of Electrical and Computer Engineering, University of California, Riverside, CA, USA
E-mails: {asadeghimobarak, hamed}@ece.ucr.edu

***Abstract*—A new optimization framework is proposed to operate a large, and price-maker generation firm in a performance-based regulation market. It takes into account various design factors such as the details about the underlying performance-based regulation market rules and Automatic Generation Control (AGC) dispatch mechanisms, as well as the *system dynamics* of generators, e.g., for the case of a steam-turbine generator. Without loss of generality, our focus is on the California Independent System Operator (CAISO) performance-based regulation market and its two available bidding components, namely *regulation capacity bidding* and *regulation mileage bidding*. Case studies are presented to gain insights about the proposed bidding method, its characterizes, and its practical implications.**

***Keywords*: Performance-based regulation market, system dynamics, transfer functions, price-maker, California ISO.**

NOMENCLATURE

i, j	Index for generators
k	Index for random scenarios
(t)	Continuous time
(s)	Complex frequency
$[\tau]$	Discrete regulation time slot
C	Superscript for regulation capacity
M	Superscript for regulation mileage
MCP	Market clearing price
r	Regulation capacity/mileage allocation
U	Regulation capacity offer
O	Regulation price offer
y	Mechanical output of generator
K	Number of random scenarios
R	Regulation capacity/mileage requirement
m	Resource-specific mileage multiplier
AGC	Automatic generation control signal
T_g, T_t	Parameters of generator transfer function

I. INTRODUCTION

Federal Energy Regulatory Commission (FERC) Order 755 [1], issued on October 20, 2011, requires Independent System Operators (ISOs) to develop pay-for-performance protocols and tariffs in wholesale electricity regulation markets to compensate regulation resources based on the *actual performance* they provide. This compensation includes a market-based capacity payment and a market-based payment for performance. The uniform market-based capacity payment should include the marginal units opportunity costs for holding capacity in reserve to provide real-time frequency regulation service. The market-based performance payment known as *mileage payment* should reflect the quantity of frequency regulation services provided by the resource when the resource is following the Automatic Generation Control (AGC) dispatch regulation signal. Many ISOs, including the California ISO (CAISO), have already adopted this new market mechanism.

Recent studies have aimed to evaluate and improve the existing performance-based regulation market from the *viewpoint of ISOs*, including PJM [2], MISO [3], or CAISO [4], [5]. They addressed some important issues such as improving the regulation market mechanism [4], properly calculating the performance of market participants [5], and properly rewarding or penalizing market participants [3]. A comprehensive survey on the existing implementations of performance-based electricity markets among different ISOs in the U.S is provided in [6].

There are also papers that seek profitable operation of regulation resources in performance-based regulation markets. For example, in [7], the authors solved an optimal bidding problem for batteries considering their life cycles. The optimal offering of flywheel energy storage units and electric vehicles are also analyzed in [8] and [9], respectively. These and other similar studies are all intended for small *price-taker* regulation resources, who cannot affect the regulation market prices.

In this paper, our goal is to optimize the operation of *large* and *price-maker* regulation resources under the CAISO performance-based regulation market rules. Specifically, we develop a new mathematical foundation to choose *capacity* and *mileage* bids. Our design is not limited to a particular resource technology. Instead, we try to understand the key underlying concepts in this new market paradigm. The main contributions in this paper can be summarized as follows:

1) A new optimization-based framework is proposed to optimally operate regulation resources in the CAISO performance-based regulation market. Unlike in [2]–[6], our analysis is from the viewpoint of market participant not that of the ISO. Also, unlike in [7]–[9], we study large, price-maker regulation resources, rather than small, price-taker regulation resources. It must be noted that price-maker operation does often happen in practice. For example, a recent study has shown that as few as six resources provided over 78% of the total regulation service to CAISO during May and June 2014 [10].
2) The proposed framework in this paper takes into account several important technical details about the CAISO performance-based regulation market, such as the AGC dispatch mechanism, that have not been previously addressed in comparable studies in [7]–[9]. The dynamic response of the producers to AGC regulation signals are

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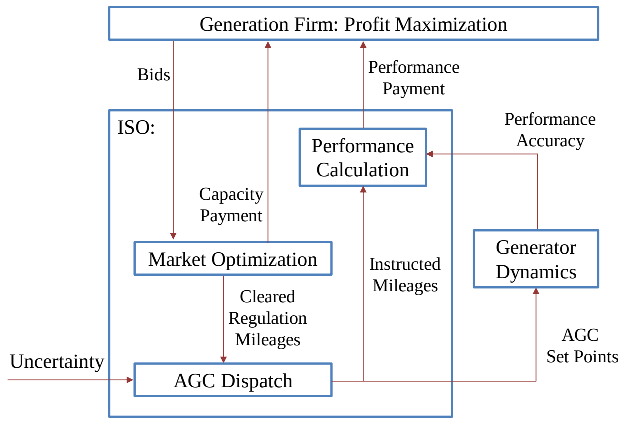

Fig. 1. The main components in our analysis and their interactions.

also modeled in details using their transfer functions.

3) Insightful results are presented using CAISO data. It is shown how the regulation capacity and mileage payments are linked together, and how they affect optimal operation. Price-maker design is also compared with price-taker design and it is shown how a generation firm can use its price-making ability to increase its profits.

II. Problem Formulation

Consider a generation firm that bids in a performance-based regulation market. In this paper, our focus is on the California ISO market , where each bid comprises two components: 1) a regulation capacity offer in MW/interval and its associated price in \$/MW/interval; and 2) a mileage price offer in \$/MW. Each market interval takes 15 minutes [4, pp. 4-6].

In each market interval, the ISO clears the *regulation capacities* and *regulation mileages* of all market participants by solving an optimization problem that seeks to minimize the overall cost of regulation, and by taking into account its estimation of the AGC signal during the upcoming market interval. In the case of the California ISO, the resolution of the AGC signal is four seconds; thus, each regulation market interval includes $15 \times 60/4 = 255$ AGC set points [4, p. 11]. Once each market interval is implemented and the actual AGC signal and the metered contribution of each regulation market participant is realized, the ISO calculates the payment to each market participant based on its performance in following the AGC signal and also based on the market outcome.

The main components in our analysis and the interactions among those components are shown in Fig. 1. Next, we will explain each component and its related mathematical models.

A. Profit Model

Suppose the generation firm of interest has $i = 1, \ldots, I$ generators. Also, unlike [7] which considered the AGC set points deterministic, their randomness is modeled in form of $k = 1, \ldots, K$ scenarios [11] knowing that they may have some predictability [12]. Let $AGC_{i,k}[\tau]$ denote the realization of the AGC set point that is sent to generator i at time

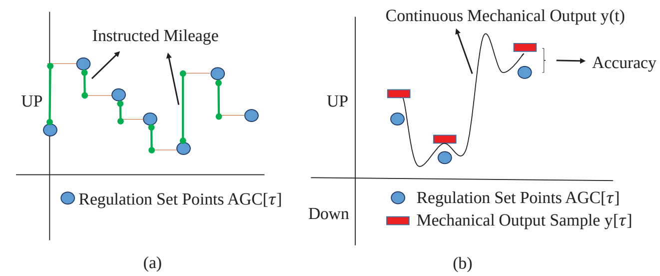

Fig. 2. An example on calculating mileage and accuracy in CAISO [6].

slot τ of length four seconds under random scenario k. The total *expected profit* for the generation firm offering only regulation up service during each fifteen minutes regulation market interval is calculated as

$$\sum_i MCP^C r_i^C + \frac{1}{K} MCP^M \times \sum_{i,k} \Bigg[\left(\sum_\tau AGC_{i,k}[\tau] - \mid AGC_{i,k}[\tau] - y_{i,k}[\tau] \mid \right) \Big/ \left(\sum_\tau AGC_{i,k}[\tau] \right) \Bigg] \times \left[\sum_\tau \mid AGC_{i,k}[\tau] - AGC_{i,k}[\tau-1] \mid \right], \quad (1)$$

where the first term is the *regulation capacity payment* and the second term is the *regulation mileage payment*. The problem formulation under regulation down service is similar. Thus, we only focus on regulation up service to avoid long equations that do not add to the technical value of the discussion.

The regulation capacity payment is obtained by multiplying the cleared regulation up capacity price MCP^C by the awarded regulation capacity r_i^C for each generator i. As for the regulation mileage payment, different ISOs may use different methods to calculate it. For the case of CAISO, the regulation mileage payment is obtained by multiplying the cleared regulation up mileage price MCP^M by a summation over the product of two terms, namely the *performance accuracy adjustment*, i.e., the first bracket, and the *instructed mileage up*, i.e., the second bracket [5]. These two terms are illustrated in Fig. 2(a) and (b). Next, we explain each term.

The performance accuracy adjustment is associated with the level of accuracy in following the AGC signal. It is calculated as sum of all AGC set points minus sum of deviations from each AGC set point. The result is then divided by sum of all AGC set points. Note that, CAISO treats positive and negative deviations *equally* [13, p. 14]. Here, $y_{i,k}[\tau]$ is the mechanical output of generator i in response to set point $AGC_{i,k}[\tau]$, at time slot τ under scenario k. If generator i follows the AGC signal exactly, i.e., $y_{i,k}[\tau] = AGC_{i,k}[\tau]$ at all time slots, then the performance accuracy adjustment is *one*. If generator i does not have any output, i.e., $y_{i,k}[\tau] = 0$ at all time slots, then the performance accuracy adjustment is *zero*. A mathematical expression for $y_{i,k}[\tau]$ will be derived in Section II-B.

The instructed mileage up is associated with the shape of the AGC signal. It is the absolute change in the AGC regulation up set points that take new values every four seconds, represented by $\mid AGC_{i,k}[\tau] - AGC_{i,k}[\tau-1] \mid$ in (1). This term indicates what mileage the ISO would *ideally* expect from generator i in each four second set point interval [13, pp. 8].

B. System Dynamics

The ability of a generator in following the AGC signal depends on its technology and physical characteristics. Without loss of generality, we consider a governor-turbine control model for each generator, where a speed governor senses the changes in its power command set points, i.e., the AGC set points, and converts them into valve actions. A turbine then converts the changes in valve positions into changes in mechanical power output, i.e., generation signal $y_{i,k}(t)$.

The governor-turbine control is often modeled as a two-state dynamic system: one state corresponds to the *speed governor* and one state corresponds to the *turbine valve position* [14], [15]. Other states may also be considered depending on the generator technology. System dynamics in *frequency domain* are then modeled using appropriate *transfer functions*:

$$Y_{i,k}(s) = G_i(s) AGC_{i,k}(s), \quad \forall i,k,s. \tag{2}$$

Here, s is the complex frequency variable and $G_i(s)$ is the transfer function of generator i. The system dynamics of generator i is modeled by a simplified steam-turbine generator model [14]. This transfer function is

$$G_i(s) = \frac{1}{(1+T_g s)(1+T_t s)}, \tag{3}$$

where there are two poles as $-1/T_g$ and $-1/T_t$. Also, $Y_{i,k}(s)$ and $AGC_{i,k}(s)$ denote the Laplace transformations of time-domain continuous signals $y_{i,k}(t)$ and $AGC_{i,k}(t)$, respectively. The time-domain continuous signal $AGC_{i,k}(t)$ can be represented in form of a weighted summation of several *unit step functions*: $u(t) = 0$ for $t < 0$ and $u(t) = 1$ for $t \geq 0$ [16, p. 22]. The weights are the AGC set points $AGC_{i,k}[\tau]$ at each time slot τ, see Fig. 2(a) for an example. We can write

$$\begin{aligned} AGC_{i,k}(t) = \sum_{\tau=1}^{225} \Big[& \left(AGC_{i,k}[\tau] - AGC_{i,k}[\tau-1] \right) \\ & u(t - 4(\tau-1)) \Big]. \end{aligned} \tag{4}$$

By taking Laplace transform from (4), we obtain

$$AGC_{i,k}(s) = \frac{1}{s} \sum_{\tau=1}^{225} e^{-4(\tau-1)s} \left(AGC_{i,k}[\tau] - AGC_{i,k}[\tau-1] \right). \tag{5}$$

From (2), (3) and (5), we have:

$$\begin{aligned} Y_{i,k}(s) = & \frac{\left(s - \frac{T_g + T_t}{T_g T_t}\right) y_{i,k}(0^-) - y'_{i,k}(0^-)}{(s + \frac{1}{T_g})(s + \frac{1}{T_t})} + \\ & \frac{\sum_{\tau=1}^{225} e^{-4(\tau-1)s} \Big(AGC_{i,k}[\tau] - AGC_{i,k}[\tau-1] \Big)}{s(1+T_g s)(1+T_t s)}, \end{aligned} \tag{6}$$

where the first term is the zero input condition response and the second term is the zero initial condition response [16, pp. 767-774]. Using *partial fraction expansion* method, see [16, pp. 767-774] and then by applying the inverse Laplace transform, the mechanical output of generator i in time domain becomes

$$\begin{aligned} & y_{i,k}(t) = \frac{T_g T_t}{T_g - T_t} e^{\frac{-1}{T_t} t} \left(-y'_{i,k}(0^-) - \frac{2T_g + T_t}{T_g T_t} y_{i,k}(0^-) \right) + \\ & \frac{T_t T_g}{T_t - T_g} e^{\frac{-1}{T_g} t} \left(-y'_{i,k}(0^-) - \frac{T_g + 2T_t}{T_g T_t} y_{i,k}(0^-) \right) + \\ & \sum_{\tau=1}^{225} \Bigg[\Big(AGC_{i,k}[\tau] - AGC_{i,k}[\tau-1] \Big) \times \\ & \left(1 + \frac{T_t}{T_g - T_t} e^{-[t-4(\tau-1)]/T_t} - \frac{T_g}{T_g - T_t} e^{-[t-4(\tau-1)]/T_g} \right) \\ & u(t - 4(\tau-1)) \Bigg]. \end{aligned} \tag{7}$$

The above expression is a continuous signal. The mechanical output of generator i at time slot τ is obtained as

$$y_{i,k}[\tau] = y_{i,k}(t = 4\tau), \tag{8}$$

see Fig. 2(b) for an example. Once we replace (8) in (1), we can express the regulation mileage payment, i.e., the second term in (1), based on the AGC set points that are sent to generator i under scenario k as well as the transfer function parameters of generator i.

C. Regulation Market Model

1) Market Optimization Problem: Once CAISO collects the regulation bids of all market participants, it solves the following regulation market optimization problem:

$$\begin{aligned}
\textbf{min} \quad & \sum_j O_j^C r_j^C + \sum_j r_j^M O_j^M && && (9) \\
\textbf{s.t.} \quad & \sum_j r_j^C \geq R^C && : \quad MCP^C, && (10) \\
& \sum_j r_j^M \geq R^M && : \quad MCP^M, && (11) \\
& r_j^C \geq 0 && \forall j, && (12) \\
& r_j^C \leq U_j && \forall j, && (13) \\
& r_j^M \geq r_j^C && \forall j, && (14) \\
& r_j^M \leq m_j r_j^C && \forall j, && (15)
\end{aligned}$$

where j is the index for all regulation resources including the I generators of the generation firm. The resource-specific mileage multiplier m_j for each generator j is a parameter that is set by CAISO using the historical data of generator j.

The objective function in (9) is the total bid-in cost of regulation up capacity and regulation up mileage. Constraints (10) and (11) indicate the market regulation up capacity requirement and the market regulation up mileage requirement, respectively. The dual variables corresponding to these constraints, shown after semicolons, indicate the regulation up capacity price and the regulation up mileage price, respectively. Constraints (12) and (13) assure operating all the regulation resources within their operational limits. Note that, U_j is in MW/interval and it is limited by the ramp rate of generator j. Constraints (14) and (15) are intended to link capacity payment and mileage payment for each resource. Specifically, from (14), the mileage reward of a resource cannot be less than its capacity reward. From (15), it also cannot be greater than the product of its regulation up capacity reward and resource-specific mileage multiplier. This is consistent with the principle of establishing a uniform clearing price for mileage that takes into consideration the expected resource performance [17]. Note that, the mileage payments that are obtained as the solutions of problem (9)-(15) are *not* financially binding because the actual mileage payments are calculated once the AGC signals are realized and the accuracy of each resource in following its corresponding AGC signal is measured.

2) AGC Dispatch Method: Let $AGC_k[\tau]$ denote the overall regulation set point at time slot τ and under scenario k that is calculated by the ISO based on the overall imbalance between supply and demand in the power system. In this section, we discuss how $AGC_k[\tau]$ is divided into several *resource-specific* AGC set points. Note that, for the generation firm of interest, the resource-specific AGC set points are denoted by $AGC_{i,k}[\tau]$ for $i = 1, \ldots, I$, see Section II-A. AGC dispatch is done using the concept of *participation factor*, which indicates the portion of $AGC_{i,k}[\tau]$ out of $AGC_k[\tau]$ [14, pp. 127-128].

The choice of participation factor may differ among ISOs. However, it is often in some way related to the regulation market outcome. That is, it depends on certain solutions of the market optimization problem in (9)-(15). In this paper, we use a variation of the method in [17, p. 12] and assume that

$$AGC_{i,k}[\tau] = \min\left\{ r_i^C, \frac{r_i^M}{\sum_i r_i^M + \sum_{j \neq i} r_j^M} AGC_k[\tau] \right\}, \tag{16}$$

where the participation factor of generator i is a fraction of its mileage over the total cleared mileage. As regulation mileage and regulation capacity are determined separately in CAISO market optimization procedure, the $\min$ function is needed in (16) to make sure that AGC set points do not exceed the cleared regulation mileage capacity r_i^C.

D. Optimal Bidding Problem

In summary, if a generation firm tends to maximize its own profit in (1), it must solve the following optimization problem:

$$\begin{aligned} &\textbf{maximize} \quad (1) \\ &\textbf{subject to} \quad (7), (8), (9) - (15), (16). \end{aligned} \tag{17}$$

The above optimization problem is a *bi-level programming problem* where the optimization variables are r_j^C, , r_j^M, O_i^C, O_i^M, $AGC_{i,k}[\tau]$, MCP^C, MCP^M, together with the dual variables of the optimization problem in (9)-(15). The constraints are with respect to not only market optimization problem (9)-(15), but also the generator dynamics (7) and the AGC dispatch mechanism (16). The optimization problem in (17) incorporates all the components that are shown in Fig. 1. Note that, we assumed the firm under study knows the market requirements and bidding information of all other bidders.

Once we follow the technique in [18], [19] and replace the linear optimization problem in (9)-(15) with its equivalent Karush-Kuhn-Tucker (KKT) conditions, the optimization problem in (17) takes the form of a class of NLP formulation named *mathematical program with equilibrium constraints* (MPEC), which can be solved using standard NLP solvers.

TABLE I
MARKET PARAMETERS FOR ILLUSTRATIVE EXAMPLE

Mileage	Generator 1	Others			Market	
	U	U	O^C	O^M	R^C	R^M
High	130	45	4.5	0.75	250	600
		50	6	0.55		
		30	5	0.9		
		60	6.78	0.45		
		80	4.8	1		
Low	130	45	4.5	0.75	250	250
		50	6	0.55		
		30	5	0.9		
		60	6.78	0.45		
		80	4.8	1		

TABLE II
MARKET OUTCOMES FOR ILLUSTRATIVE EXAMPLE

Mileage	Generator 1				Others		Market	
	r_1^C	r_1^M	Accuracy	Revenue	r^C	r^M	MCP^C	MCP^M
High	130	246.7	93.8	883	45	100.8	4.82	0.98
					50	227.5		
					0	0		
					0	0		
					25	25		
Low	130	130	98.5	754	45	45	5.8	0
					0	0		
					0	0		
					0	0		
					75	75		

III. Case Studies

Consider a performance-based regulation market with the same number of generators and resource-specific mileage multiplier of the dominant resources in CAISO, i.e., six generators with $m = 2.7,\ 2.24,\ 4.55,\ 2.3,\ 2.5$, and 3.6 [10]. Generator 1 is of interest to submit optimal bids. The dynamics of this generator are modeled by $T_g = 0.5$ sec and $T_t = 8$ sec. Other parameters are $y_1(0^-) = AGC_{1,k}[1]$, and $y_1'(0^-) = 0$.

A. High versus Low Mileage Cases

For the case studies in this section, we first generated two random scenarios using CAISO AGC data in [20]. The average mileages are 682.1 MW and 20 MW, respectively. The market parameters under these two random scenarios are shown in Table I. The market outcome under the proposed optimal bidding approach is given in Table II. We can see that when the mileage requirement is high, Generator 1 seeks to maximize its profits by obtaining mileage revenue, where r_1^M is high. As the market mileage requirement decreases, Generator 1 may earn less revenue from mileage. Hence, it seeks to increase the regulation capacity revenue. Accordingly, it uses its price-making ability to increase MCP^C while decreasing MCP^M. In the low mileage case, Generator 1 offers *very high* regulation capacity bid and *very low* regulation mileage bid. Nevertheless, the ISO still clears its bids because the cleared mileage and cleared capacity are linked together, through the market optimization problem in (9)-(15).

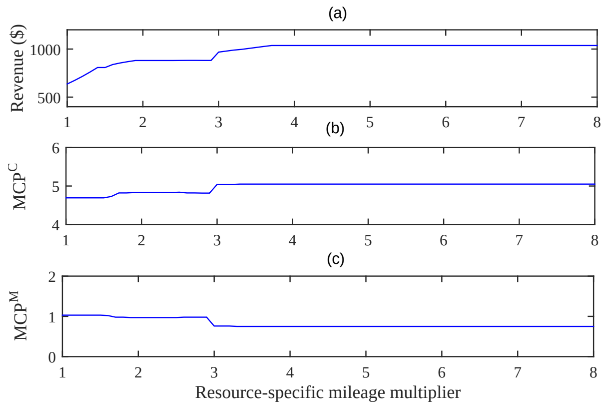

Fig. 3. The impact of changing resource-specific mileage multiplier: (a) total revenue, (b) regulation capacity price, (c) regulation mileage price.

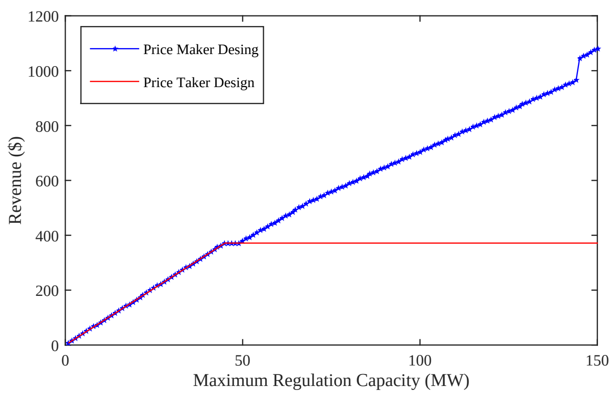

Fig. 4. Comparing price-taker and price-maker bidding. The need for a price-maker design is more evident as the capacity of the resource increases.

B. Resource-Specific Mileage Multiplier

Next, we consider the high mileage scenario and assume that all parameters are the same as the ones in Section III.A. Since the rewarded regulation capacity and mileage are *linked* together through m, it is expected that the revenue of a generator changes as m changes. This is shown in Fig. 3(a). It is interesting to see that the revenue does *not* change for larger amount of $m \geq 4$. Moreover, as m increases from 1 to 3, the generator can exercise more its price-making ability and change the market clearing prices to maximize its revenue as shown in Figs. 3(b) and (c).

C. Price Taker versus Price Maker Bidding

The comparative results are shown in Fig. 4 for the high mileage case. As expected, the two designs are similar when the resource capacity is small. However, as the resource capacity increases, exploiting price-making capability can significantly increase the revenue from the regulation market.

IV. CONCLUSION AND FUTURE WORK

A new design framework was proposed for optimal bidding of a large, price-maker generation firm in the CAISO performance-based regulation market. The generation firm seeks to maximize it profits considering the payment rules in this market as well as the details about AGC dispatch mechanisms and the system dynamics of its own generators. This problem is modeled as a bi-level optimization problem. Several case studies are presented using CAISO AGC market data to assess our design as well as the impact of different mileage requirements, resource-specific mileage multipliers, and price-making bidding abilities.

This paper can be extended in several directions. The problem can be analyzed for other performance-based regulation markets such as MISO. The new solution methods can be obtained to transform the formulated nonlinear program to a more tractable problem. Larger market with different case studies may also be analyzed. The model with more details on power system dynamics or the model with the co-optimization of energy and ancillary services can be considered.

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