# Market Design for Grid Regulation Services with Energy Storage

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**Executive Summary**

Energy storage has long been identified has a key enabling technology for large scale penetration of renewable energy sources in the electric grid, particularly for an ancillary service called "regulation", or sometimes "frequency regulation". To date, however, storage has made at best modest inroads in actual practice. Among the various reasons for the slow adoption is that energy markets today are not structured to recognize and pay for the unique benefits, nor account for the unique limitations, that energy storage technologies bring to the table. Fundamentally, today's market applies the same $/hr per MW market clearing price to all resources, regardless of their unique benefits or limitations. Various authors have proposed incentives to address this fundamental market design weakness; such incentives, however, are sensitive to arbitrarily selected parameters which are subjective and hence subject to bias from special interests. The present white paper examines the limitations of today's regulation market structure, and proposes a formulation of the grid regulation problem from which market design and control strategies naturally derive. The problem formulation explicitly accounts for the benefits and limitations of energy storage and other classes of resources. The resulting market design and control strategies have lower aggregate operating costs for the balancing authority than current approaches for the same "quality of regulation", and optimally price dissimilar energy resources by their relative contributions toward good regulation.

## 1 Introduction

In the bulk electric grid, generators are paid to produce energy, and consumers pay for the energy they consume. The electric grid is an energy transport system, not an energy storage system. Consequently, at each point in time, the same amount of energy must be generated (or extracted from storage) as is absorbed (consumed or placed into storage).

In each geographical region there is a "balancing authority", an entity whose role is to keep the production and consumption of energy in balance. In deregulated energy markets this is accomplished by operating several inter-related markets: day-ahead energy market, the standby reserves market, the synchronous reserves market, real-time energy market, and the regulation market.

The present white paper is concerned with the design and operation of the "regulation" market. A good in-depth introduction to regulation markets is given in [1].

"Regulation", which is sometimes also called "frequency regulation", is the process of keeping the short-run (minute-by-minute) operation of the grid in balance. Minute-by-minute changes occur too quickly for market mechanisms to work reliably; when power is needed immediately to keep the grid in balance, it is not workable to wait 20 minutes for an auction to take place to decide who will provide the power. Instead, the balancing authority engages a set of resources ahead of time to be ready to respond on demand minute-by-minute to maintain balance. This is sometimes called "frequency regulation" because grid frequency is continuously affected by the balance; frequency increases if generation exceeds consumption, and decreases if consumption exceeds generation.

### 1.1 Market Design

Many different technologies have been evaluated for grid regulation. Examples are:

- Generators (thermal, natural gas)
- Supercapacitors
- Batteries
- Load Demand Response
- Flywheels

At present, generators are the most widely used resource for regulation, but it is widely recognized that efficient limited energy storage resources have much to offer.

Typical regulation markets today treat all resources used for regulation as essentially interchangeable. That is, they are treated as a single asset class for purposes of markets and pricing. If the market clearing price for regulation is $50/hr per MW, then that clearing price applies to all regulation resources, whether supercapacitors, batteries, or thermal generators.

There is a widely recognized fundamental problem with this market design: the resources' performance is vastly different – 1 MW of regulation from a thermal generator is entirely different than 1 MW of regulation from a supercapacitor energy storage system.

Thermal generators can produce energy for indefinite periods of time, but they have relatively slow "ramp rates" for increasing or decreasing the power they are generating. By contrast, supercapacitor storage banks can charge and discharge extremely quickly, but are limited in the total quantity of energy they can deliver on demand. Sometimes this issue is called "sustainability" – different resources can sustain a response for different lengths of time.

Suppose supercapacitors could be made very inexpensively, for example so they could be offered in large quantities to the market at a price of $10/hr per MW, but that the thermal generator could only be offered at $50/hr per MW or more. Then the market would choose all supercapacitors. But there is a technical problem with this --- a mix of 100% supercapacitors and 0% thermal generators cannot possibly meet the technical requirements of regulation. Supercapacitors respond quickly, but it is necessary to have resources available for regulation which can absorb or provide energy over longer time periods.

This does not, however, indicate there is no role for supercapacitors. Indeed, their rapid response times make them a good candidate for meeting *part* of the technical requirement for regulation, but not all of it. Similarly, unlimited availability of inexpensive slow responding generators may result in adequate regulation because of their slow response times.

In the long run, slow responding generators and fast responding limited energy storage resources cannot be priced the same per MW. The market design MUST reflect the different technical capabilities.

Energy storage will not penetrate the market appreciably until a workable solution to this market design issue becomes well-established.

### 1.1.1 Terminology

| Term | Definition |
|---|---|
| ACE | Area Control Error – This is the quantity that grid regulation seeks to control to approximately zero. |
| PACE | Processed Area Control Error – This is the power demand signal that the balancing authority sends to regulation resources. |
| Regulation | Regulation is the process of maintaining the energy balance of the grid by injecting energy into the grid or removing energy from the grid in order to keep ACE close to zero. |
| MCP | Market Clearing Price - A price, measured in $/hour per MW of regulation. Resources offered to the regulation market at less than the market clearing price are selected, and resources offered at a higher price are not. |

### 1.1.2 Market Design - Incentives

A recent conference at FERC on compensation in frequency regulation markets [2]discussed the issue of pay for performance.

One question asked was "are the markets willing pay for better regulation?" This question is based on the intuition that faster response should be worth something. There's the idea that faster response will result in "better regulation", and that "better regulation" should have some economic value. But there's no widespread notion of who is willing to pay a premium for "better regulation", and how good is good enough.

The issue of differing technical capabilities is widely recognized in the industry; it is recognized that some kind of pay for performance is needed, but as yet there is no consensus on how pay for performance should be structured. Certain incentives have been proposed by various parties to address the shortcomings of today's market design, typically by augmenting the basic market design with "incentives". Three incentives were discussed in some detail in the FERC conference:

- Pay for "Mileage"

  New England ISO has had some success with a "pay for mileage" incentive that pays a resource a premium based on how much it *changes* in response to the regulation demand signal. This incentive biases the markets in favor of technologies with fast response times.

- Pay for "Opportunity Cost"

  The panel also discussed a "pay for opportunity cost" incentive that biases the markets in favor of unlimited energy generators, which must curtail their energy production in order to participate in the regulation market. This incentive would prevent the markets from pricing slow-responding unlimited energy resources out of the market if fast responding limited energy resources became widely available.

  Panelist Andrew Ott of PJM International in particular discussed using the opportunity cost incentive for generators to make the decision whether to supply energy or regulation a cost-flow neutral decision; in this line of thinking, the decision should be made to optimize grid reliability, rather than economically.

- Pay for "Accuracy"

  A "pay for accuracy" incentive that pays based on how closely the resource tracks the regulation demand signal. This incentive is similar to "pay for mileage" in that it favors fast response times. Some make the case that pay for accuracy and pay for mileage are essentially redundant.

### 1.1.3 Market Design – Asset Classes

Another approach to address the same fundamental market design problem is to split the regulation market into two separate markets. There could be one market for slow responding unlimited energy resources, and a separate market for fast responding limited energy resources.

| Slow Unlimited Energy | Fast Limited Energy |
|---|---|
| Thermal generators | Supercapacitors |
| Load Demand Response | Batteries |
| | Flywheels |

The two asset class market design in principle addresses the core issue with the single asset class design, but with two problems:

- The asset classes are not independent

  Availability of fast responding limited energy resources reduces the need for slow responding unlimited energy resources, and vice versa. But neither eliminates the need for the other entirely.

  The more fast responding resources are available at low cost, the fewer slow responding resources are needed. Similarly, the more slow responding resources are available at low cost, the fewer fast responding resources are needed.

  Hence the markets are inherently coupled – the market clearing price for slow responding unlimited energy resources would be lower – but not zero – if fast responding limited energy resources are widely available at low cost.

  For this to work, some mechanism would be required to moderate between the two markets.

- The technical distinction between the asset classes must be arbitrarily decided.

  Someone needs to decide what response is "slow" and what response is "fast". Similarly, someone needs to decide what constitutes a "limited energy" resource versus an "unlimited energy" resource. For example, a NAS battery has a charge / discharge time on the order of 4 or 5 hours – is this a "limited energy resource" or an "unlimited energy resource"?

In theory, the two asset class market design should eliminate, or at least reduce, the need for the ad hoc incentives; it addresses the same underlying issues in a less arbitrary way.

## 2 Discussion

Our view is that each of the incentives from Section 1.1.2 has good valid rationale and addresses a fundamental weakness in the one-asset class regulation market design. However, we also view each of the incentives as an ad hoc response to these weaknesses. Each requires a somewhat arbitrary "rate of pay", and is therefore susceptible to political bias, which may not be best for the grid as a whole, rather than being driven from purely economic and technical factors.

Similarly our view of the two asset class solution is that while it addresses the most fundamental problem with market design, it too requires arbitrary distinctions to be made, which necessarily favor certain technologies others, and therefore is similarly susceptible to political bias.

Our view is that the goal of the regulation market is to achieve a specified quality of grid regulation at minimum cost, without biasing for or against any particular technologies.

In the remainder of this paper, we posit that the "quality of regulation" can be measured by $\sigma_{ACE}$, the standard deviation of the Area Control Error (ACE), and that the goal of the regulation market is to find the minimum cost feedback control for which $\sigma_{ACE} \leq \sigma_{REF}$. The upper limit, $\sigma_{REF,}$ represents the standard deviation of ACE which provides adequate stability margin to the grid.

We show how this problem can be formulated and solved mathematically, and how the market design and control strategy naturally fall out of this formulation. Further, we show that the resulting market design does not bias for or against any technology, other than rewarding contributions to the reduction of ACE. Finally, we show how this problem formulation addresses the issues raised by the various “incentives” discussed earlier, and how it explicitly finds optimal pricing of dissimilar assets.

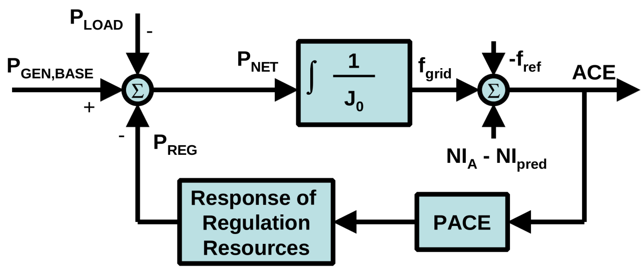
## 2.1 Technical Problem Formulation

First, we provide a quantitative rationale for defining the goal of grid regulation markets as “finding the lowest cost means to provide adequate regulation.” This section is a technical discussion in the language of feedback control systems engineering.

If excess power is generated in the control area, the grid frequency increases; excess power tends to increase grid frequency:

$$P_{NET} = J_0 \frac{df_{grid}}{dt}$$

The feedback block diagram below shows the influence of load and regulation feedback on ACE.




If the response of regulation resources is ideal (i.e. fast and accurate … simply a gain of “1”), and If PACE is simply $K_p \cdot ACE$ for some feedback gain $K_p$, then the frequency domain transfer function from $P_{LOAD}$ to $ACE$ is

$$\frac{ACE(s)}{P_{LOAD}(s)} = \frac{-1}{J_0 s + K_p}.$$

To a control systems engineer, this shows that in the ideal case $\sigma_{ACE}$ can be made arbitrarily small by making $K_p$ arbitrarily large. That is, if the control objective were to minimize the variance of *ACE*, then it would be accomplished by making $K_p$ arbitrarily large – aggressive, immediate, high gain regulation.

Of course, the idealization above does not account for delay in the feedback path. In reality, the control path includes the delay for the balancing authority to signal the regulation resources and for those resources to respond. Typically the signaling delay is on the range of 5 seconds, and the delay for resources to respond can range from seconds to minutes.

If we model the delay in the system response, it is easy to show that the feedback system becomes unstable if $K_p$ is too large. Indeed, there is an optimal value of $K_p$ which minimizes $\sigma_{ACE}$ when actual delays are taken into account.

Unfortunately, formulating the problem as optimization of $\sigma_{ACE}$ still doesn’t adequately represent the economic tradeoffs. In other words, in answer to the question “are the markets willing to pay for better regulation”, the answer is maybe a little, but only to a point.

If optimization of $\sigma_{ACE}$ were truly the objective, the solution would be to minimize delay in the feedback path. It would call for reducing signaling delay from today’s 4 seconds down to less than 1 second, and would call for many fast responding resources to be used for feedback. It is intuitively clear that this would be cost prohibitive; minimizing $\sigma_{ACE}$ is not the true objective.

Rather, the economic problem is to find the lowest cost means to provide “adequate” regulation. Mathematically, we propose to define “adequate regulation” as the condition:

$$\sigma_{ACE} \le \sigma_{REF} ,$$

where $\sigma_{REF}$ is chosen to provide adequate stability margin for the grid. In what follows, we will show how to quantitatively predict the tradeoff between $\sigma_{ACE}$ and the cost of regulation, and hence turn the objective “lowest cost to provide adequate regulation” into a well-defined mathematical problem.

## 2.2 Quantitative Model

This section presents a mathematical model of the grid regulation dynamics which allows us to predict $\sigma_{ACE}$ from the response characteristics of the regulation resources. Once we can predict $\sigma_{ACE}$ from regulation resource, we can show the relationship between $\sigma_{ACE}$ and cost of regulation.

The closed loop system is comprised of three subsystems, each of which is modeled separately: (a) load statistics, (b) response of regulation resources, and (c) ACE dynamics.

### 2.2.1 Load Statistics

Predictive models of aggregate load are well-established in the industry, but even the best predictive models cannot predict the fine-grained random changes in load that occur on short time scales. The predictive models are used to determine the base setpoints of power generators; grid regulation resources are use to respond to the unpredictable, fine-grained random changes.

Still, the statistics of the fine-grained random changes in load can be modeled; the statistics are used to determine how much regulation is needed – for example 1% of the predicted base load.

W use variable $p(t)$ to represent the random portion of load at time $t$:

$$P_{LOAD}(t) = P_{LOAD,PREDICTED}(t) + p(t)$$

Signal $p(t)$ is a zero mean random process with a known correlation time constant, $\tau_p$.

$$E\{p(t) \cdot p(t+T)\} = \sigma_p^2 e^{-|T/\tau_p|}$$

Here "E" represents the expected value of a random variable.

For convenience of calculation, we represent u as a discrete time Gaussian random process driven by white noise, with sample interval $T_s$:

$$p_{k+1} = \alpha \cdot p_k + w_k$$

Here wk is the "white noise" signal:

$$E\{w_k w_{k+N}\} = \begin{cases} \sigma_w^2, N = 0 \\ 0, N \neq 0 \end{cases}$$

This formulation gives:

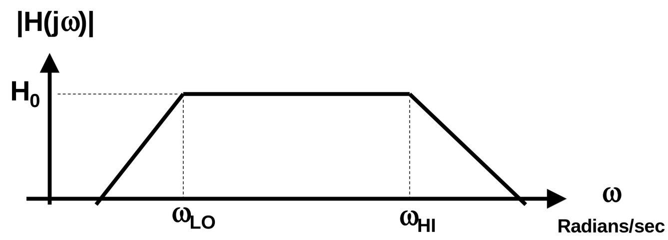
$$E\{p_k \cdot p_{k+N}\} = \alpha^{-|N|} \cdot \frac{\sigma_w^2}{1-\alpha^2},$$

which gives a correlation time constant given by

$$\alpha = e^{-|T_s/\tau_p|}$$

### 2.2.2 Response of Regulation Resources

A resource used for grid regulation is parameterized by its response time, its maximum power level, and by the length of time it can operate at maximum power. This is a non-linear system, but it has a region within which its operation is linear. We can represent its operation within the linear region as a band-limited linear system, as represented by the following Bode plot:




The resource's response time is parameterized by its high frequency cutoff point, $\omega_{HI}$. The maximum power can be represented by the amplitude of the frequency response within its normal band of operation, $H_0$, measured in MW. Last, the maximum length of time the resource can operate at maximum power is parameterized by $\omega_{LO}$. The longer the resource can sustain its output, the smaller the value of $\omega_{LO}$.

A supercapacitor is a narrowband device –it has a very fast response, but depletes its energy quickly. That is, the ratio of $\omega_{HI}$ to $\omega_{LO}$ is small. A NAS battery is a wider band device – it has a very fast response, and can continue to discharge for multiple hours. That is, the ratio of $\omega_{HI}$ to $\omega_{LO}$ is large. A thermal generator has a slower response, but can continue operating virtually indefinitely ($\omega_{LO}$ is very small).

This frequency response is obtained by the following linear system:

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix}_{k+1} = \begin{bmatrix} 1-\beta & 0 \\ -\mu & 1-\mu \end{bmatrix} \cdot \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}_k + \begin{bmatrix} \beta \\ \mu \end{bmatrix} u_k,$$

$$y_k = \begin{bmatrix} 0 & H_0 \end{bmatrix} \cdot \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}_k$$

where $\beta = e^{-\omega_{LO}T_0}$, and $\mu = e^{-\omega_{HI}T_0}$. The input, $u_k$, is the regulation signal from the balancing authority, with a value between -1 and +1. The output, $y_k$, is the actual power output of the resource, measured in MW. For notational convenience, we write this in matrix / vector notation, using subscript $n$ to represent the $n^{th}$ of many resources, as

$$z_n(k+1) = A_n \cdot z_n(k) + S_n \cdot B_n \cdot u_n(k)$$

$$y_n(k) = S_n \cdot H_n \cdot z_n(k)$$

In this equation, $S_n$ is 1 if the resource is selected by the market; otherwise it is 0. The total response from all regulation resources taken together is

$$y(k) = \sum_{n=1}^{N} y_n(k)$$

Combining all the regulation resources into a single set of state equations for the response of regulation resources, we obtain:

$$z(k+1) = A \cdot z(k) + S \cdot B \cdot u(k)$$

$$y(k) = H \cdot z(k)$$

In this equation $S$ is a matrix of 1's and 0's, indicating which resources are selected by the market and which are not.

### 2.2.3 State of Charge & Energy Loss

The reader should note that limited energy resources are limited not only by the duration of a discharge or charge event, but also by "state of charge"; when the stored energy has been depleted, it must be recharged before it can be called upon again for "up" regulation. Similarly once it reaches 100% state of charge it must be partially depleted before it can be called upon again for "down" regulation.

Similarly, limited energy resources are not 100% efficient; they are net consumers of energy over the long run. Neither the charge management function, nor the energy losses are represented in the quantitative model above. Indeed, these effects are real and must be handled for regulation to work properly.

The "charge management" dynamics could be controlled directly by the balancing authority via the $u_k$ command sequence, or indirectly by incorporation into the resources' internal control logic. For the purposes of this paper, the two approaches are equivalent; regardless, recharge dynamics are required and they will have essentially the same effect on aggregate response in either case, assuming the rate at which they are recharged is similar.

For simplicity of presentation, and not to distract from the essential proposition of this white paper, we have not incorporated charge management and energy loss dynamics into the quantitative models presented here. Nevertheless, they would be incorporated into models if the principles laid out in this paper are to be applied in practice. The adaptation is straightforward – the 2-state model presented in Section 2.2.2 would be augmented with a 3rd state, representing "state of charge" (SOC), and a term for feedback of SOC into the performance model. We will present the extended linear model in another forum.

### 2.2.4 ACE Dynamics

A discrete time formulation of system dynamics will prove more convenient for further analysis. Consequently, we represent the ACE dynamic model discussed above in continuous time into the following discrete time model:

$$v(k+1) = v(k) - \Phi \cdot [y(k) + p(k)],$$

where

$$\Phi \equiv \frac{T_s}{J_0},$$

and $v(k)$ is the ACE at time step $k$, $p_k$ is the random portion of system load, and $y_k$ is the power delivered to the grid from regulation resources.

### 2.2.5 Combined System Model

Last, note that $\sigma_{ACE}^2 = K_p^2 \cdot \sigma_u^2$, and we've constrained $u(k)$ to the range [ -1, +1 ]. Assuming signals are Gaussian, we can choose

$$K_p = \frac{1}{3\sigma_{REF}},$$

which gives a 99.7% probability of $u(k)$ being within the [-1, +1] range. In other words, on average 0.3% of the time $u(k)$ will be at the upper or lower limit.

The closed loop dynamic equations for the entire system, including load statistics (section 2.2.1), response of regulation resources (section 2.2.2), and ACE dynamics (section 2.2.4), form a linear discrete time system of dynamic equations with known parameters, with a "white noise" input:

$$\begin{bmatrix} p \\ z \\ v \end{bmatrix}_{k+1} = \begin{bmatrix} \alpha & 0 & 0 \\ 0 & A & K_p B \\ -\Phi & -\Phi \cdot H & 1 \end{bmatrix} \cdot \begin{bmatrix} p \\ z \\ v \end{bmatrix}_k + \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \cdot w_k$$

The method to calculate the variance of signals in linear system such as this is well known. (See Section 5.2 for a brief overview.) The equations for variance are linear, and can therefore be calculated using standard numerical methods.

The ACE (i.e. $v(k)$) is one of the signals in the system of equations, hence $\sigma_{ACE}^2$ is one of the elements in the state correlation matrix, which be readily calculated using a standard linear equation solver.

## 2.3 Optimization Algorithm

The problem statement provided in this white paper requires a non-trivial algorithm for finding the optimum asset mix in the most general case. We have developed an effective algorithm for solving it, but the algorithm is not presented here, as it could distract from the fundamental contribution of this paper, which is the problem formulation itself.

## 2.4 Cost of Regulation

Each of the energy resources costs the balancing authority a fixed price per hour. Hence the cost of regulation is the sum of resource prices:

$$\text{Total Cost per hour} = \sum_{n=1}^{N} S_n \cdot C_n ,$$

where $C_n$ is the cost per hour to use resource $n$. As before, $S_n$ is 1 if resource $n$ is selected by the market, and 0 if it is not.

## 2.5 Examples

### 2.5.1 Example #1 – Two resource types

Let's apply the proposed market design to a hypothetical case where there are two asset classes: (a) thermal base energy generators, and (b) supercapacitors. All quantities in the example are intentionally chosen as unrealistic – the point is to see how market design influences the results, rather than what the specific hypothetical results are.

For the example, we assume the following parameter values:

$T_s =$ 4 seconds

$\sigma_p =$ 50 MW

$\sigma_{REF} =$ 0.010 Hz

$J_0 =$ 6000 Hz per MW per second

We assume the thermal generators' offering to the regulation market are characterized as follows:

$H_0 = 1$ MW

$\omega_{HI} =$ 3x10$^{-3}$ radians/sec [5 minute ramp rate]

$\omega_{LO} =$ 1x10$^{-5}$ radians/sec [1 day duration]

$C_n =$ \$1/hr per MW

We assume the supercapacitor resources are characterized as follows:

$H_0 = 1$ MW

$\omega_{HI} =$ 2x10$^{-1}$ radians/sec [5 second ramp rate]

$\omega_{LO} =$ 1x10$^{-2}$ radians/sec [100 second duration]

$C_n =$ \$2/hr per MW

Following are the results of this example for four different market selections:

| Market | $S_1$ | $S_2$ | $\sigma_{ACE}$ | Cost |
|---|---|---|---|---|
| Thermal generator only, min $\sigma_{ACE}$ | 225 | 0 | 0.576 | \$225/hour |
| Supercapacitor only | - | - | *Unstable* | *Unstable* |
| Combination – minimum $\sigma_{ACE}$ | 3025 | 200 | 0.035 | \$3525/hour |
| Combination – Minimum cost for $\sigma_{ACE}$ < 0.576 | 45 | 18 | 0.576 | \$81/hour |

These results illustrate quantitatively the intuition that (a) the using fast limited energy resources only could result in an uncontrollable system, (b) fast limited energy resources used in combination with slower unlimited energy resources can achieve extremely tight regulation but at significant cost penalty, (c) that the length of time a resource can sustain its output affects its contribution to $\sigma_{ACE}$, (d) and that fast limited energy resources used in combination with slower unlimited energy resources can significantly lower the cost of obtaining a prescribed level of regulation

The proposed market design would achieve the \$81/hour cost in this example.

**<u>Comparison to using "incentives"</u>**

Let's consider whether / how this cost might be accomplished using today's typical market design, augmented by one or more of the incentives introduced earlier.

Since the supercapacitor resource costs more per MW than the thermal generator's \$1 / MWh, in order to obtain a 45 / 18 mix of thermal generator to supercapacitor storage system, it would be necessary decrease the cost of operating the superconductor system such that it can compete at a market clearing price of \$1 / MWh.

If an incentive is derived which favors the superconductor technology by \$0.99 / MWh, then the market will *still* select all thermal generators. But if the incentive favors the superconductor technology by \$1.01 / MWh, then the market will select all superconductor storage systems --- which would be unable to regulate the grid.

Suppose instead the superconductor energy storage systems are not offered to the market at exactly $2 / MWh, but rather at a range from $1.8 / MWh to $2.2 / MWh. In this case, there is a particular incentive value which will result in the optimum mix of thermal generators to superconductors. However, it should be clear that the optimum incentive is very sensitive to small changes in the distribution of offering prices of the resources.

In other words, while the incentive system can be used to bias the market toward an optimum mix, the resulting resource mix and quality of regulation can be extremely sensitive to the level of the incentive and to the distribution of offering prices.

By contrast, the proposed market design mechanism is relatively insensitive to such small changes, and will find an optimum resource mix in any case.

### 2.5.2 Example #2 – Fast Generators

Consider the same example above, but where two unlimited energy resources are competing, with the same parameters and cost per MWh as above, except that one is fast responding: $\omega_{HI} =$ 6.5x10$^{-2}$ radians/sec (15 second ramp rate).

| Market | $S_1$ | $S_2$ | $\sigma_{ACE}$ | Cost |
|---|---|---|---|---|
| Nominal generator only, min $\sigma_{ACE}$ | 225 | 0 | 0.576 | $225/hour |
| Fast generator only, min $\sigma_{ACE}$ | 0 | 340 | 0.060 | $340/hour |
| Combination – minimum $\sigma_{ACE}$ | 900 | 200 | 0.056 | $1100/hour |
| Combination – Minimum cost for $\sigma_{ACE}$ < 0.576 | 19 | 16 | 0.562 | $35/hour |

Again this example shows that optimizing the combination of dissimilar resources can lower aggregate cost appreciably.

## 2.6 Market Clearing Price

The concept of Market Clearing Price is well-established in the regulation markets. In a commodity market, all resources are treated as interchangeable, and hence the price at which they are offered to the market is the only factor in their selection.

The Market Clearing Price (MCP) is the threshold price; resources offered to the market at a price less than the MCP are selected by the market, and resources offered at a higher price are not.

The familiar concept of Market Clearing Price depends on the interchangeability of resources, so that price per MW is the only factor in their selection. The market selection algorithm is then to select resources from least expensive to most expensive until enough resources are selected to give adequate regulation.

The market formulation we propose, however, does not treat resources as interchangeable, and as a result can't use this simple selection algorithm. Dissimilar resources compete directly, but not solely on the basis of cost per MW; they also compete based on the degree to which they assist in reducing $\sigma_{ACE}$.

This means, for example, that a slow-responding unlimited energy resource may be selected by the market at a price of $50/hr per MW, while a fast responding storage device may not be selected even at a price of $25/hr per MW. Hence with this optimal market design, the concept of Market Clearing Price must either be defined differently, or jettisoned entirely.

Since the Market Clearing Price concept of is deeply embedded in the industry, our position is that the concept needs to be retained, but defined in a new way. The new definition must be equivalent to the traditional definition in the special case where all resources are indeed interchangeable.

Traditionally the same Market Clearing Price applied to the entire market. In the new definition, it is defined on a resource-by-resource basis:

Defn: The Market Clearing Price for a particular resource is the threshold price per MW below which the resource would be selected by the market, and above which the resource would not be selected by the market.

The change in definition is making it specific to the resource, rather than applying to the entire market.

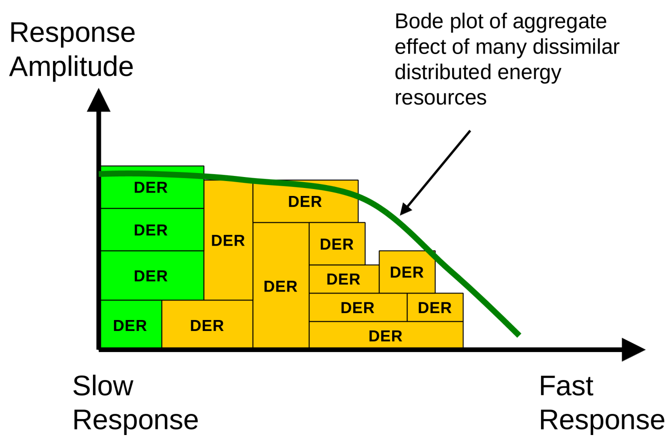
In the special case where all resources are interchangeable, then they all have an equal Market Clearing Prices, and it can be computed using a simple sorting algorithm. In the more general case where resources are not interchangeable, dissimilar resources will have different Market Clearing Prices, and a more complex algorithm is required to compute it.

## 2.7 Market Clearing Price Density

Under certain mathematical assumptions regarding linearity, the market clearing price can be computed as a spectral density. That is,

$$MCP_k = \int \rho(\omega) \cdot H_k(\omega) \cdot d\omega,$$

where $\rho(\omega)$ is a market clearing price density at frequency $\omega$, and $H_k(\omega)$ is the frequency response of resource $k$. This feature of the market clearing price makes for a convenient visualization of the control system / market mechanism, as illustrated below.




## 3 Conclusions

It is clear and well-understood in the industry that some kind of pay-for-performance is necessary for energy storage to penetrate the regulation market appreciably.

While ad hoc incentives have been used with some success in markets, we showed that the resulting aggregate quality of regulation can be very sensitive to the parameters of the incentive.

We have presented an alternative market design based on a quantitative model which has only one arbitrarily manually selected parameter – namely the target quality of regulation, $\sigma_{ACE}$. The proposed market design selects an optimum mix of resources, even if those resources have dissimilar performance characteristics. Further, it prices those resources by their relative contribution toward maintaining $\sigma_{ACE}$.

Our essential proposition is that by using a quantitative formulation, the market design will be less subjective, less sensitive to tuning parameters, hence robustly lower in aggregate cost for a given quality of regulation.

### 3.1 Next Steps

- Validate the quantitative model:

  (a) Establish good parameters for load statistics in practice.

  (b) Validate the linear frequency response model for limited energy resources,

  (c) Validate the linear frequency response model for ramp-rate limited resources.

  (d) Validate the relationship between grid frequency and net power. (i.e. ACE dynamics)

  (e) Validate that condition $\sigma_{ACE} \leq \sigma_{REF}$ is a suitable definition for "adequate regulation".
- Quantify cost savings which the proposed market design / control strategy could bring using actual performance numbers and offering prices.
- Apply alternative market designs to hypothetical test cases and compare results
- Implement the optimization algorithm in software for large numbers of market participants.
- Tradeoffs for integrating ESS into renewable generation plants (PV and Wind).

## 4 References

[1] Brendan J. Kirby, Frequency Regulation Basics and Trends, ONRL/TM-2004/291, December 2004.

[2] Transcript of OFA Technical Conference before the Federal Energy Regulatory Commission, Washington, DC, May 26, 2010.

[3] Alec N. Brooks, Vehicle-to-Grid Demonstration Project: Grid Regulation Ancillary Service with a Battery Electric Vehicle, research report for CARB, December 10, 2002.

## 5 Appendix

### 5.1 Plausibility of Linear Models

We are using linear models to represent dynamics of resources which clearly have some non-linear characteristics. While not essential for the conceptual problem formulation, we do use the linear models for the proposed computational method.

Some justification is required for the use of the linear model. The essential dynamic characteristics of the resources are:

- Ramp rate limit.
- Limit on maximum power delivered to the grid or received from the grid.
- The maximum duration during which a response can be sustained.

All three characteristics play critical roles in the overall contribution the resource makes toward regulation. Since all actual resources are non-linear in the small scale, but exhibit these same kinds of limitations, we posit that a linear model approximating these characteristics will represent the actual tradeoffs in practical applications.

We recommend follow-up using simulation studies to validate this position.

## 5.2 State Variance in Linear Systems

In a stable linear system driven by white noise, the steady state variance of the state vector can be compute analytically.

Let's say the state equations are given by

$$x(k+1) = F \cdot x(k) + G \cdot w(k),$$

Where $w(k)$ is a zero mean uncorrelated (white noise) random process. Define the correlation matrix of vector $x(k)$ as

$$\Sigma_k = E\left\{x_k \cdot x_k{}^T\right\}$$

Then

$$\Sigma_{k+1} = E\left\{x_{k+1} \cdot x_{k+1}{}^T\right\}$$

$$\Sigma_{k+1} = E\left\{(F \cdot x(k) + G \cdot w(k)) \cdot (F \cdot x(k) + G \cdot w(k))^T\right\}$$

$$\Sigma_{k+1} = E\left\{\left(F \cdot x(k) \cdot x(k)^T F^T + G \cdot G^T \sigma_w^2\right)\right\}$$

$$\Sigma_{k+1} = F \cdot \Sigma_k{}^T F^T + G \cdot G^T \sigma_w^2$$

The interaction for the correlation matrix $\Sigma_k$ converges for large k if the linear system is stable. Hence it reaches a steady state given by:

$$\Sigma = F \cdot \Sigma^T F^T + G \cdot G^T \sigma_w^2$$

This final equation is linear in the elements of $\Sigma$, and can therefore be solved using ordinary linear equation solver.

The resulting matrix, $\Sigma$, is the steady state correlation matrix for vector $x(k)$.

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