# Frequency Regulation with Mileage Payments: Is a Competitive Market Always the Winner?

Ran Zhang[1], Chen Zhao[1], Dan Zheng[1], and Wenqian Jang[2,3](✉)

[1] Electric Dispatch and Control Center, Guangdong Power Grid Company Ltd, Guangzhou, Guangdong, China

[2] School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, China
wenqianjiang@link.cuhk.edu.cn

[3] Shenzhen Institute of Artificial Intelligence and Robotics for Society, Shenzhen, Guangdong, China

**Abstract.** The advancement in distributed generation units and storage systems is stimulating a vigorous market for frequency regulation. Nevertheless, as identified by the Federal Energy Regulatory Commission, the un-paced payment structure in use may not well recognize the frequency regulation providers' performance, which warrants incorporating the "mileage payment" into the structure. Surprisingly, our theoretical analysis illustrates that such a new form of payment, if not designed carefully, may further prevent the independent system operators from achieving cost-effective frequency regulation. We compare two scenarios to support this argument - a competitive market and a regulated one. Counter-intuitively, due to the difficulty in the concise short-term load prediction in a reasonably large window, the competitive market is not the winner. We further establish the performance guarantee for the regulated market. Extensive simulation results confirm our theoretical analysis and demonstrate our approach's feasibility in the current AGC framework.

**Keywords:** Frequency regulation · Mileage payment · Model predictive control · Optimization

## 1 Introduction

Automatic Generation Control (AGC) for frequency regulation has served to balance generation and load and ensure that the frequency is kept close to its nominal value well in the past. However, the advancement in distributed generation units and storage systems, in combination with the increased variability introduced by a higher penetration of renewable resources has led to how to more fairly compensate the resources participating in frequency regulation for their services. As required by the recent Federal Energy Regulatory Commission (FREC) Order 755 [1], the independent system operators (ISOs) need to incorporate mileage payments to recognize the performance of the resources in frequency regulation. The mileage payment intends to "reward those resources that perform more regulation service instead of simply netting the total amount


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of energy injected by the resource" [2], which is not captured by the existing capacity payment (which is used to compensate the lost opportunity cost) and the net energy payment/charge. If a cost-effective AGC is pursued, the limited ramping capacities of the resources render the decision-making at each time slot depends on the past decisions and possibly the future. The introduction of mileage payments is expected to further such coupling in time.

The classic approach to tackling optimization with time coupling constraints and the objective function is to perform model predictive control (MPC) [3]. Unfortunately, implementing MPC requires the prediction of the disturbances in the system, which in the case of AGC is captured by the area control error (ACE) signal. This signal is tough to predict reliably. In this paper, we consider a simplified steady-state linear model between the frequency deviation, the generation outputs and the load variations. Luckily, the generation outputs are the control variables, and recent works on concise short-term (1-min resolution) load prediction [4] shed light on the way to perform the challenging prediction. The proposed algorithm constantly achieves an error between 1 and 7% for 1-min resolution prediction. This warrants the MPC scheme to perform frequency regulation with all the three kinds of payments.

Albeit classic and promising, the cost-effectiveness of MPC in the power system is less concerned. After all, performance and cost-effectiveness both matter. In this paper, we compare two scenarios:

- a competitive market where each resource submits bids for the mileage payment,
- a regulated market where the ISO provides a fixed price for mileage payment.

The theoretical analysis suggests that, due to the difficulty in the very short-term load prediction in a reasonably large window, only the regulated market can provide the necessary, cost-effective guarantee, whereas, surprisingly, the competitive market can be manipulated by the market players. The counterintuitive conclusion seems consistent with market power manipulation [5–7] in the conventional real-time market.

## 2 Related Work and Contributions

Unlike voltage control [8] and conventional frequency regulation schemes, the understanding of mileage payments started only recently. For example, Papalexopoulos et al. proposed a comprehensive analysis of frequency regulation's performance-based pricing (including mileage payment) in [9]. In [10], Taylor et al. introduced a price and capacity competition with the imbalance fee, conceptually similar to mileage payments. Besides rising interests in the market design with mileage payment, empirical studies to understand the impact of different auxiliary regulation services also emerged: e.g. Lu et al. evaluated the flywheel potential for providing regulation service considering the mileage payment in [11]. Wu et al. explored using a risk-limiting economic dispatch scheme to optimize the dispatch and provision of flexible ramping products in [12], and the impact of flexible ramping products on a bid-based market is further analyzed in [13, 14]. Different from the existing works, which were mostly based on the single time slot optimization, our paper attempts to understand how the mileage payment affects the cost-effective frequency regulation in a dynamic setting and employs an MPC approach to tackle the challenge.

Our work also fits into the growing body of research on utilizing MPC for frequency regulation. Atic et al. presented a decentralized MPC approach to performing regulation in [15]. Gao et al. investigated the impact of introducing the corresponding mileage cost to the renewables for causing fluctuations in the system by the MPC method in [16]. Venkat et al. extensively compared various MPC frameworks and proposed a cooperation-based MPC for the current AGC system in [17]. With the popularity of plug-in electric vehicles, interesting MPC-based frequency regulation frameworks with time-varying resources (the PHEVs) were discussed in [18, 19]. In contrast, our work is motivated by the introduction of mileage payment to frequency regulation, making the theoretical analysis more challenging.

This paper seeks to answer the following key question: *is it possible to design a performance guaranteed market for frequency regulation with mileage payment?*

Towards answering the question, in Section III, we first propose the problem formulation using the MPC approach and identify the analytical difficulty in a straightforward formulation. Then, in Section IV, we compare the competitive market design and the regulated one. After that, we perform extensive case studies for the two kinds of markets in both the linearized simplified model and the swing dynamic model in Section V. Finally, our concluding remarks and directions for future work are discussed in Section VI.

## 3 Problem Formulation

### 3.1 Steady-State Linear Model

While swing dynamics can efficiently capture the system evolution, it becomes hard to develop effective control strategies when considering the ramping constraints. A more complicated cost function will make the control strategy design even harder. To better understand the mileage payment's impact on the cost-effective frequency regulation, we consider a simplified steady-state linear model, where we take advantage of the fact that primary frequency control is in place to stabilize the frequency. Denote the set of frequency regulation resources by $\mathcal{N}$, and resource n's regulation contribution at time t by $g_n^t$. Then, in steady state, the frequency deviation $\Delta f(t)$ from its nominal value is linear in the load deviation from the load prediction used in the energy dispatch, denoted by $\hat{d}^t$. Mathematically, $\Delta f(t)$ will stabilize at

$$\Delta f(t) = \frac{\sum_{n \in \mathcal{N}} g_n^{t-1} - \hat{d}^t}{\gamma} \tag{1}$$

where

$$\gamma = \sum_{p \in \Omega_P} \frac{1}{R_p} \cdot \frac{P_{p,r}}{f_r} \tag{2}$$

and $\Omega_P$ is the set of entities participating in primary frequency control [20], $R_p$ is the speed droop and $P_{p,r}$ the nominal power of entity $p$ and $f_r$ is the nominal frequency (here 60 Hz).

### 3.2 MPC Formulation

Since frequency regulation aims at dealing with minor fluctuations in the power system, in contrast to the energy dispatch problem, it is reasonable to consider frequency regulation in an electricity pool model. Most deregulated electricity markets have separate markets for regulation-up and regulation-down services. Here, to better differentiate the two services, we explicitly define the frequency regulation contribution as the difference between the frequency regulation resource's actual power output and its nominal power decided by the energy dispatch. If such difference (denoted by $g_n^t$ in this paper) is positive, we consider the resource is offering regulation up service, whereas negative regulation contribution leads to regulation down service. We take the regulation-up service market as an example for our analysis. All the discussions can be applied to the regulation-down service market similarly by replacing the non-negative constraint on $g_n^t$ with the non-positive constraint.

At time slot $h$, assume we could obtain the load deviation prediction $\hat{d}^t$ in a window of size $W$, i.e., $t \in \mathcal{W}^{\mathrm{h}} \doteq \{\mathrm{h}, \mathrm{h}+1, \cdots \mathrm{h}+\mathrm{W}-1\}$. The length of one time slot could be 15 s or even less. Thus, if a cost-effective control is pursued, then the ISO seeks to solve the following problem:

$$\min \sum_{t \in \mathcal{W}^{\mathrm{h}}} \sum_{n \in \mathcal{N}} (c_n g_n^t + \beta_n |g_n^t - g_n^{t-1}|) \tag{3}$$

$$s.t. \left| g_n^t - g_n^{t-1} \right| \leqslant \Delta g_n, \forall n \in \mathcal{N}, \forall \mathrm{t} \in \mathcal{W}^{\mathrm{h}}, \tag{4}$$

$$0 \leqslant g_n^t \leqslant \overline{g}_n, \forall n \in \mathcal{N}, \forall \mathrm{t} \in \mathcal{W}^{\mathrm{h}}, \tag{5}$$

$$\sum_{n \in \mathcal{N}} g_n^t = \hat{d}^t, \forall t \in \mathcal{W}^{\mathrm{h}}, \tag{6}$$

The decision variables in the optimization problem (3)-(6) are $g_n^t$'s: frequency regulation resource $n$'s regulation contribution [MW] at time $t$. The parameters, on the other hand, are.

- $c_n$: net energy bid [$/MW] of regulation resource $n$;
- $\hat{d}^t$: demand deviation from demand prediction value used in the energy dispatch [MW] at time $t$;
- $\overline{g}_n$: resource $n$'s maximal regulation up capacity [MW];
- $\Delta g_n$: resource $n$'s ramping limit [MW/15 s].

Note that $g_n^0$'s are considered as given values. Constraint (4) enforces each regulation resource's ramping limit. Constraint (5) ensures the capacity constraints are met, and the last constraint represents the power balance condition at each time slot. We do not consider the co-optimization determines it with the energy bids in the real time energy dispatch market. Thus, the capacity payment is simply a constant in this optimization stage.

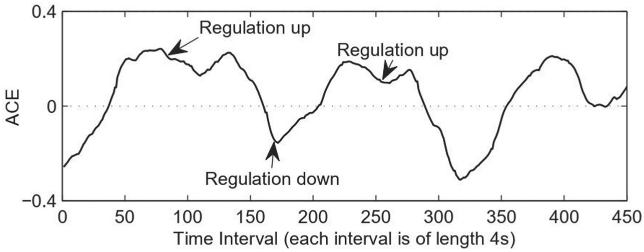



**Fig. 1.** The ACE signal in PJM [22]

### 3.3 Relaxation

Though straightforward, the performance analysis (e.g., comparing with the offline optimal) of such a 1-norm MPC formulation is very challenging: even in the unconstrained case, due to the lack of an explicit closed-form expression for the control law [21]. Figure 1 shows the 30-min actual ACE signal in PJM. If the regulation resources accurately follow the control signal, their generation outputs ought to follow this trace. Note that the regulation up and regulation down services switch over time frequently. This implies that during each course of regulation up/down period, the total mileage of ramping up equals that of ramping down. This motivates considering the following alternative formulation to (3) - (6):

$$\min \sum_{t\in\mathcal{W}^{\mathrm{h}}} \sum_{n\in\mathcal{N}} (c_n g_n^t + 2\beta_n[g_n^t - g_n^{t-1}]^+)$$

$$s.t. \text{ Constraints } (4) - (6) \tag{7}$$

where $[x]^+ \doteq \max\{0, x\}$. We can only consider the mileage payment when regulation resources ramp up and neglect the ramp down. By doubling the mileage payment, the overall payment for each regulation resource over the long run remains the same.

Another issue is that constraint (6) may be too strict. The ramping constraints may often render the optimization problem infeasible. Thus, we consider the following relaxation:

$$\min f\left(g_n^t, \forall n, \forall t\right) + M \sum_{t\in\mathcal{W}^{\mathrm{h}}} |\sum_{n\in\mathcal{N}} g_n^t - \hat{d}^t|$$

$$s.t. \text{ Constraints } (4) \text{ and } (5) \tag{8}$$

where

$$f\left(g_n^t, \forall n, \forall t\right) = \sum_{t\in\mathcal{W}^{\mathrm{h}}} \sum_{n\in\mathcal{N}} (c_n g_n^t + 2\beta_n[g_n^t - g_n^{t-1}]^+) \tag{9}$$

and $M$ is a large number to trade-off between cost-effectiveness and system performance. When $M \to \infty$, optimization (8) will essentially schedule the power outputs to minimize the mismatch in the system. On the other hand, when $M$ is reasonably large, it reflects the ISO's interest in having a cost-effective solution.

### 3.4 Illustrative Prototype

Before moving to the performance assessment, we want first to observe how $M$ affects the optimal solution's structure and illustratively exemplify the trade-off with a simple prototype. We use a window size of 3 and assume perfect load deviation prediction.

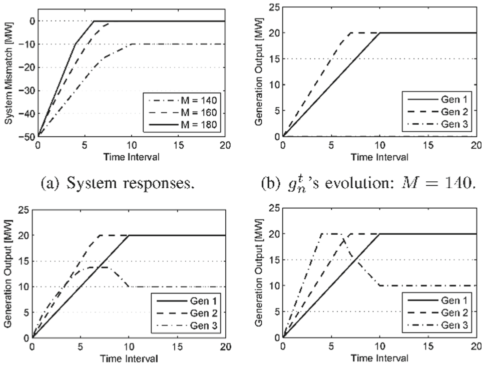
**Table 1.** Generator information for the prototype system

| | $c_n$[\$/MW] | $\beta_n$[\$/MW] | $\Delta g_n$ [MW/15 s] | $g_u$[MW] |
|---|---|---|---|---|
| Gen 1 | 50 | 20 | 2 | 20 |
| Gen 2 | 70 | 15 | 3 | 20 |
| Gen 3 | 120 | 10 | 5 | 30 |

The prototype system has three generators as frequency regulation resources. Table 1 shows their parameters. When experiencing a 50 MW step load increase, all the three generators are expected to contribute to compensate for such mismatch. When $M$ is relatively small ($M = 140$), since ramping up the third generator is too expensive (at the cost of $120 + 10 \times 2 = 140$), the MPC approach will not schedule it to perform regulation, as shown in Fig. 2(b). This leads to a supply–demand mismatch of 10 MW, as shown in Fig. 2(a). This case intuitively demonstrates the critical point when selecting $M$: if

$$M \leqslant \max\{c_n + 2\beta_n\} \tag{10}$$

the system reliability, in terms of utilizing all the resources to recover the mismatch, is not guaranteed. As long as $M > \max\{c_n + 2\beta_n\}$, the MPC approach ensures system reliability, as illustrated in the other two cases. However, a larger $M$ ($M = 180$) will compensate for the mismatch faster, whereas a smaller $M$ ($M = 160$) will perform the regulation in a more cost-effective way, though the final generation output profiles (after 225 $s$, i.e., $h \geqslant 15$) for the two cases are the same. We will return to this prototype in the case study to better understand our approach.




(a) System responses. (b) $g_n^t$'s evolution: $M = 140$.

(c) $g_n^t$'s evolution: $M = 160$. (d) $g_n^t$'s evolution: $M = 180$.

**Fig. 2.** Prototype system to highlight the impact of $M$

# 4 Performance Assessment

Following (8), we compare the competitive market design and the regulated one. We differentiate these two cases by how the $\beta_n$'s are set. If the resources are allowed to bid their own $\beta_n$'s, we term such case the competitive one. On the contrary, if the ISO directly sets the same $\beta_n$ for all resources, we term such case the regulated one.

## 4.1 Competitive Case

We first consider a competitive scenario. It is seemingly trustworthy that if we allow a competitive market, then by selecting the most efficient regulation resources, the market will achieve maximal efficiency. Let us consider the following simple counterexample, where there are only two regulation resources, A and B, and the ramping and generation capacity constraints are not the primary concerns. Resource A submits a bid consisting of its net energy bid $c_a$, and mileage bid $\beta_a$. Resource B, the more cost-efficient one, tries to manipulate the mechanism by submitting its actual net energy bid $c_b < c_a$, and an extremely high $\beta_b \gg \beta_a$. Thus, when encountering a step load change, the ISO using the MPC approach, with a limited size of prediction window, will be reluctant to choose B due to the high mileage payment, which will lead to an average cost of $c_a$. However, suppose the ISO knows all the future information (i.e., the load disturbance is a step change). In that case. it will instead choose B regardless of the high mileage payment since such "capital cost" will amortize over time and eventually lead to an average cost of $c_b$.

This example highlights the daunting part of the MPC design. Indeed, as popular as it is, MPC has limited abilities. The malicious resource can choose to report false information about the mileage cost and directly affect the net energy payment. This might be tackled if the ISO does not select these malicious market players in the first place. However, the current practice - a co-optimization between the energy and frequency regulation bids - does not consider mileage bids. This is large because there are still no mileage bids. The deeper reason is that it is hard to foresee the fluctuations for the entire

15 min (or even one hour) when performing the co-optimization in the real-time energy dispatch.

To this end, alarmingly to the ISOs, it is not wise to design a competitive market for the frequency regulation with mileage payment. In the example, regulation resource B risks losing profits when reporting the wrong information, but this can be rational and reasonable if the two regulation resources collude together to achieve a better total payoff. Though a detailed discussion is beyond the scope of this paper, we want to stress that such a circumstance is not a purely theoretical fantasy, which will never happen in practice.

### 4.2 Regulated Case

In a regulated scenario, where all the $\beta_n$'s are the same, the ISO is neutral in selecting different resources to perform frequency regulation in mileage payments. Thus, the performance of MPC, in this case, is almost the same as the performance where there is no mileage payment and enjoys a $(1 + O(1/W))$ competitive ratio, which is the ratio between our approach's performance and the offline (with $W = \infty$) approach's performance [23].

**Theorem 1:** The regulated MPC is $1 + \frac{2\beta}{W \min c_n}$ competitive.

This is a direct result of [24]. We want to stress that, Theorem 1, in no way, implies that the competitive market cannot perform as well as the regulated one (in fact, it is often better); rather, since we cannot obtain the load deviation over a long time horizon, the competitive market is easier to manipulate and thus does not enjoy the performance guarantee. To this end, if the ISO were to employ an MPC approach to achieve the cost-effective dispatch, the theoretical analysis suggests a regulated market for mileage payment.

## 5 Case Study

In this section, we test our MPC approach for 200-time slots. The regulation demand profile is the scaled PJM's AGC signal [22], as shown in Fig. 3.

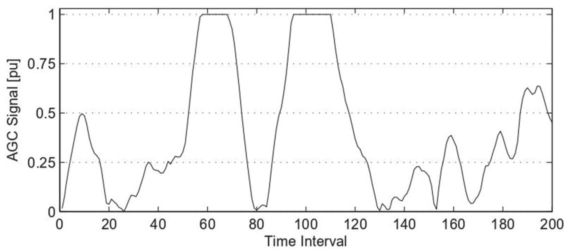
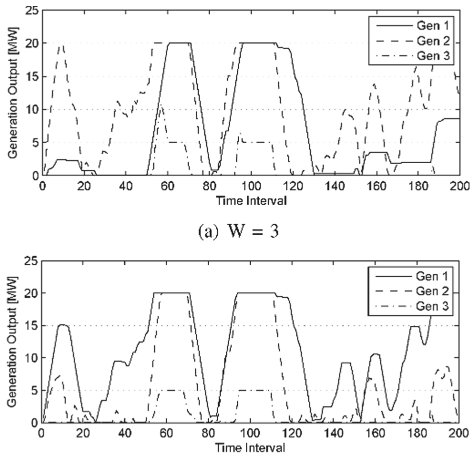



**Fig. 3.** PJM sample AGC signal

### 5.1 Competitive Market: Price Manipulation

First, we consider the prototype system. Now, generator 1, the most cost-effective one, tries to manipulate the regulation service market by submitting an extremely high mileage bid of $50/MW. The peak demand deviation is scaled to 45 MW. With a window size of 3, Fig. 4 shows the three generators' output traces, which confirm our theoretical discussion: the ISO is reluctant to schedule generator 1.

No surprise, in the optimal off-line dispatch ($W = \infty$), generator 1 provides more regulation contribution because of its low net energy cost. It is worth noting that the manipulation can be relieved by increasing the window size, as demonstrated in Fig. 4, where we use a slightly larger window size, $W = 5$, and the generation output traces change dramatically.




(a) W = 3

(b) W = 5

**Fig. 4.** Manipulation evolution of $g_n^t$'s output

### 5.2 Competitive *v.s.* Regulated Market

**Table 2.** 10 generator parameters

| n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $c_n$ | 46 | 47 | 48 | 49 | 50 | 51 | 52 | 70 | 80 | 120 |
| $\overline{g}_n$ | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| $\Delta g_n$ | 2.1 | 2.2 | 2.3 | 2.4 | 2.5 | 2.6 | 2.7 | 3.5 | 4 | 6 |

Next, we extensively compare the two kinds of markets. We extend the simulations to a 10 generators system. Table 2 shows the generators' parameters. We consider three

**Table 3.** Mileage bids for 10 generators

| n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Case R | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| Case M | 40 | 40 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Case C | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 20 | 30 | 45 |

cases of mileage bidding mechanisms shown in Table 3: Case R represents the regulated case; Case M is the competitive case with manipulation; and Case C is the truthful competitive case. Note that the mileage bids summation over all generators again remains the same for different cases ($200/MW). Trade-off $M$ is set to be 140. Figure 5 displays the trend of total payments with the increasing window size $W$. From the results we can tell that:

- The total payment decreases as the window size increases.
- Case R is better than Case M but is worse than Case C. Again; this shows that if we can ensure a truthful competitive market, then the competitive market can perform very well.

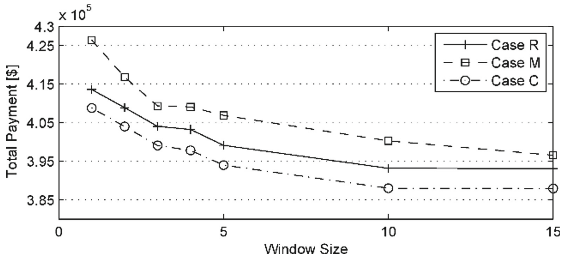



**Fig. 5.** Total payments for different cases

### 5.3 Swing Dynamics

Next, we study our MPC approach's performance on an interconnected system with swing dynamics. This demonstrates that, though our analysis is focused on the linearized model, our approach is feasible in the AGC framework and performs well. A 4-area system, as in Fig. 6 is considered. The parameters for the generators are listed in Table 4, where $M_j$, $D_j$, and $|V_j|$ stand for generator inertia, damping constant, and voltage magnitude at each area; the others are constant parameters corresponding to generator governor control and ACE-based AGC.

The mileage bids for all generators are 30$/pu, and we do not compare the net energy payment/charge here. All the generators' outputs are bounded from -0.5 to 2.5pu and

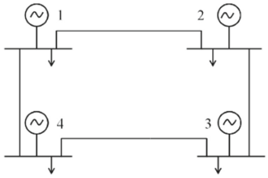



**Fig. 6.** Diagram for 4-areas Interconnected System

**Table 4.** Generator parameters for swing dynamic analysis [25]

| Area | $M_j$ | $D_j$ | $\lvert V_j \rvert$ | $T_j$ | $R_j$ | $B_j$ |
|---|---|---|---|---|---|---|
| 1 | 3 | 1 | 1.045 | 4 | 0.05 | 2 |
| 2 | 2.5 | 1.5 | 0.98 | 4 | 0.05 | 3 |
| 3 | 4 | 1.2 | 1.033 | 4 | 0.05 | 2 |
| 4 | 3.5 | 1.4 | 0.997 | 4 | 0.05 | 3 |

have a maximum ramp rate of 0.5pu. The nominal values for generation and load of all areas are set as 1pu, and a step change of load occurs at area 4. The time interval for the simulation is 0.01 s, and the tradeoff for MPC approach is chosen as $M = 140$. We employ a window size of 3.

The MPC plant includes the relaxed AGC model Eq. 8 and the linearized swing dynamics constraints (Eqs. (1) - (3) in [25]). The power change command at each generator is the control variable. The frequencies, generator mechanical power output and line power flows are state variables. The load (area 4) is treated as input disturbance. The MPC decision process solves a linear optimization problem at each step and then applies the control variables to the current step. The initial state variables are obtained from the optimization results from the last step, i.e., we assume the system model is the same as the MPC plant model. The simulations are done in MATLAB, and the optimization is optimal for every time step according to the solver *linprog*.

The dynamics of the frequencies, power change command, and mechanical power outputs for the four areas using ACE-based AGC (left) and MPC-based AGC (right) are displayed in Fig. 7. The mileage payment for these two approaches is compared in Table 5. From the results, we can tell that the MPC approach can smooth the frequency dynamics with much less regulation mileage.

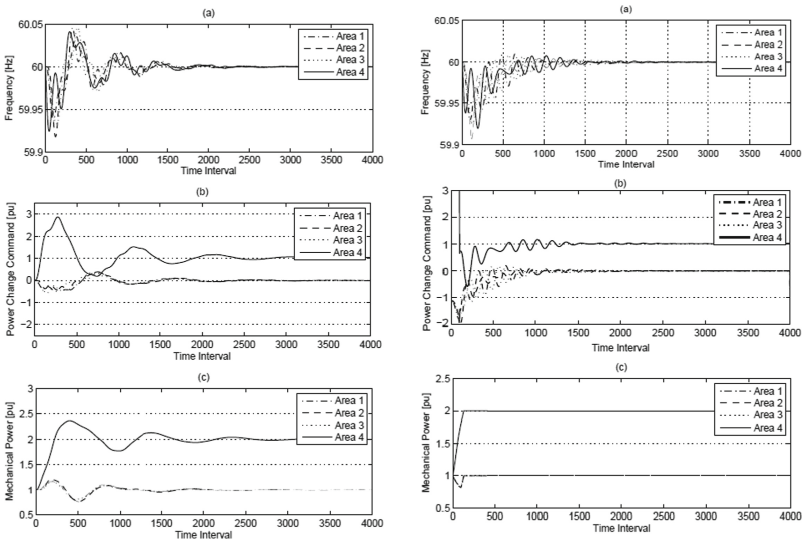



**Fig. 7.** The ACE-based (left) and MPC-based (right) AGC: (a) System Frequencies, (b) Power Change Command, (c) Mechanical Power Output

**Table 5.** Mileage payment for interconnected system [$]

| Area | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| ACE-based | 15.55 | 16.00 | 13.91 | 40.93 |
| MPC-based | 4.67 | 4.56 | 4.70 | 29.85 |

# 6 Conclusions and Future Work

The impact of mileage payments on the frequency regulation system design may be far-reaching. This paper compares the two kinds of potential markets for frequency regulation with mileage payments: the competitive and regulated markets. Theoretical analysis and simulation results suggest that the competitive market may not be the winner in the near future. This is not a denial of the competitive market. A suitable mechanism in practice is not about having the perfect plan. Instead, it involves working out the advantages of different options. Thus, we reckon that a capped bidding mechanism, the most commonly used in the electricity market, might again be the most desirable option for the mileage bidding.

This paper can be extended in various directions. For instance, we have not included the swing dynamics in the theoretical analysis, which will make our results more practical. Also, we would like to consider the decentralized or distributed MPC for frequency regulation with mileage payments. Such an approach may better suit the future power system with the large volume of participating regulation resources.

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