Toward Combining Intra-Real Time Dispatch (RTD) and AGC for On-Line Power Balancing

Marija D. Ilić, Xiaoqi Yin
Dept. of Elec. & Comp. Eng. Carnegie Mellon University Pittsburgh, Pennsylvania 15213 Email: milic@ece.cmu.edu, xiaoqi@andrew.cmu.edu

Qixing Liu
Power Dispatching and Control Center China Southern Power Grid Guangzhou, Guangdong, P.R.China Email: liuqx@csg.cn

Yang Weng
Department of Electrical and Computer Engineering Carnegie Mellon University Pittsburgh, Pennsylvania 15213 Email: yangweng@andrew.cmu.edu

Abstract—In this paper we propose first a predictive adaptive intra-RTD dispatch comprising: (1) Intra-RTD non-zero mean predictor which utilizes historic data about various uncertainties to predict the most likely non-zero mean imbalances; and, (2) Adaptive controller for non-zero mean intra-RTD imbalances using two-stage robust optimization. The result of applying these methods sequentially at the beginning of each RTD interval is the least-cost robust adaptation of RTD schedules in anticipation of the most likely non-zero mean imbalances. We illustrate how this proposed predictive adaptive intra-RTD dispatch can be implemented for a typical hour. Second, only hard-to-predict near-zero-mean imbalances are compensated using Automatic Generation Control (AGC). The basic conclusion is that a combination of predictive adaptive intra-RTD and recently proposed Enhanced-AGC (E-AGC) should be used for the least cost on-line balancing of non-zero mean and zero mean imbalances, respectively.

I. INTRODUCTION

This paper is motivated by the need for systematic low-cost balancing and pricing of intra-RTD imbalances. To start with, we observe that the basic sources of uncertainties creating these power imbalances have changed significantly and are likely to change as the role of system users in supply demand balancing evolves. In the past (independent) system operators (I)SOs have been able to predict the system demand quite accurately within less than 1% error, and have had full control of dispatchable generation, resulting in near zero-mean imbalances within the dispatching intervals. This is no longer the case since new uncertainties are created by both responsive demand and intermittent resources; this makes it very hard to predict the actual net system demand. Moreover, once fully dispatchable power plants are no longer owned and operated by the same entity responsible for balancing the system. In particular, the latter has led to significant deviations in electricity markets between RTD schedules sent to the power plants, on one side, and the actual power generated during the dispatch interval for which the commitment is made, on the other side. These deviations are a combination of poor governor response and intentional failures to produce what is scheduled. These uncertainties present qualitatively different challenges to the (I)SOs in both regulated and deregulated industry. Unless monitored and managed systematically, their effects will be highly undesirable and may lead to: (1) the need for expensive storage; (2) higher electricity prices to the end users; (3) inefficient utilization of slower resources; and, (4) hard to differentiate value of very fast resources from slow, less responsive resources.

To overcome these problems we propose in this paper to manage these diverse uncertainties by carefully combining predictions about the most likely intra-RTD deviations by the system users, with an optimization method capable of adjusting RTD schedules to account for these likely deviations. We pose the problem of predictive adaptive intra-RTD balancing using a small hypothetical system in Section II. In Section III we describe one possible approach to predicting non-zero mean deviations using historical data about actual response of specific generators. The output from the non-zero mean intra-RTD imbalance predictor is directly used as the input to the two-stage robust optimization described in Section IV. In this section, a two-stage robust optimization is formulated as one possible method for adaptive control of the non-zero mean intra-RTD imbalances. In Section V we compare the outcome of predictive adaptive intra-RTD control with the result of real-time balancing using recently proposed E-AGC. Finally, in Section VI, we summarize preliminary findings, state open questions, and recommend possible next steps.

II. THE PROPOSED PROBLEM FORMULATION OF INTRA-RTD SUPPLY-DEMAND BALANCING

We start by considering a small 5 bus system shown in Figure 1. We assume that there are two types of generators in the system: slow generators connected to buses 1, 2 and 3, and fast ones on buses 4 and 5, all with linear cost functions. The marginal costs of generators 1 through 5 are 80,88,100,258,261 ($/p.u.), respectively. The predicted system demand is shown in Figure 3a and it is assumed to be the same as actual except for the near-zero mean demand fluctuations created by intermittent resources connected to bus 3. It is

![Figure 1: A 5-Bus Test Power System](image-url)
participate in a ramp-rate limited real time dispatch (RTD), which is being done every 5 minutes. However, these slow generators do not dispatch what they have committed in RTD [1], i.e. given generation schedule \( P_S \); their actual generation \( P_S \) deviates from schedule by \( \Delta P_S \), which lies in the region \( \Omega := [\Delta P_{S,min} , \Delta P_{S,max}] \). Figure 2 shows the 1-month data for actual and scheduled generation of 3 slow generators. Note that generators tend to generate less power than scheduled. Based on these hypothetical historical data, the (I)SO can obtain the predicted region of deviation \( \hat{\Omega} \), and thus have a better knowledge of the behavior pattern of the slow generators. We note that the actual output of power plants have a better knowledge of the behavior pattern of the slow \( \hat{\Omega} \) than scheduled. Based on these hypothetical historical data, the 1-month data for actual and scheduled generation of 3 slow \( \hat{\Omega} \) can make intra-RTD generation adjustment. In the rest of the paper, we use the sequence \( \hat{\Omega} \), which lies in the region \( [\Delta P_{S,min} , \Delta P_{S,max}] \), is the difference between the scheduled power generation \( P_{S,t} \) and the actually measured power generation \( \hat{P}_{S,t} \) on the \( i \)th generator. \( \hat{P}_{S,t} \) is the measured power generation vector, equal to the summation of actual power generation \( P_{S,t} = P_{S,t} + \Delta P_{S,t} \). The Gaussian noise \( W_t \sim N(0, \sigma) \) is used to represent those near-zero mean fluctuations, contributed by intermittent resources, etc. We consider a linear state space model for historical data with time index \( k: \Delta P_{S,k} = A \Delta P_{S,k-1}, z_k = P_{S,k} - P_{S,k} = \Delta P_{S,k} + W_k, \) where matrix \( A \) is the state transition matrix. The goal in this paper is to learn the matrix \( A \) using historical data described in Section II above.

III. INTRA-RTD NON-ZERO MEAN PREDICTOR USING HISTORIC DATA

In the Intra-RTD model, we are given the historical scheduled power \( P_{S,t} \) and the (hypothetical) measured power generation \( \hat{P}_{S,t} \) for generator \( i \) as on the left of Figure 5. Their relationship can be expressed as \( \hat{P}_{S,t} = P_{S,t} + \Delta P_{S,t} + W \), where \( \Delta P_{S,t} \), which lies in the region \( [\Delta P_{S,min} , \Delta P_{S,max}] \), is the difference between the scheduled power generation \( P_{S,t} \) and the actually measured power generation \( \hat{P}_{S,t} \) on the \( i \)th generator. \( \hat{P}_{S,t} \) is the measured power generation vector, equal to the summation of actual power generation \( P_{S,t} = P_{S,t} + \Delta P_{S,t} \). The Gaussian noise \( W_t \sim N(0, \sigma) \) is used to represent those near-zero mean fluctuations, contributed by intermittent resources, etc.

\[ \Delta P_{S,k} = A \Delta P_{S,k-1}, z_k = P_{S,k} - P_{S,k} = \Delta P_{S,k} + W_k, \]

where matrix \( A \) is the state transition matrix. The goal in this paper is to learn the matrix \( A \) using historical data described in Section II above.

A. Expectation-Maximization (EM) Algorithm

The problem of intra-RTD balancing is the one of scheduling additional resources needed to compensate the significant non-zero mean imbalance left as shown in Figure 3b. Because most generators produce less power than scheduled, total demand is larger than actual total supply. This will, if not balanced in intra-RTD real time, create unacceptable frequency deviations as shown later in Section V.

\[ \hat{P}_{S,k} = (P_{S,k} + \Delta P_{S,k}) \]

The problem of intra-RTD balancing is the one of scheduling additional resources needed to compensate the significant non-zero mean imbalance left as shown in Figure 3b. Because most generators produce less power than scheduled, total demand is larger than actual total supply. This will, if not balanced in intra-RTD real time, create unacceptable frequency deviations as shown later in Section V.

\[ \hat{P}_{S,k} = (P_{S,k} + \Delta P_{S,k}) \]

The problem of intra-RTD balancing is the one of scheduling additional resources needed to compensate the significant non-zero mean imbalance left as shown in Figure 3b. Because most generators produce less power than scheduled, total demand is larger than actual total supply. This will, if not balanced in intra-RTD real time, create unacceptable frequency deviations as shown later in Section V.
step, together with the new observation \((\hat{P}_{S,k} - P_{S,k})\), we can evaluate the Gaussian marginal for \(\Delta P_{S,k}\) having mean \(\mu_k^{bw}\) and covariance \(V_k^{bw}\).

The Kalman Filter above is a forwarding algorithm that is optimal in obtaining current state estimate by using the past and current measurements. However, since all future measurements are more or less dependent on the past state, a better estimate can be achieved by conducting a backward (“bw”) algorithm resulting in \(\mu_k^{bw}\) and \(V_k^{bw}\) \([4]\).

2) Maximization (M) Step: As a summary of E-step for the M-step, we rewrite the results above in the following form

\[
E[\Delta P_k] = \mu_k^{bw}, \quad E[\Delta P_k(\Delta P_k)^T] = V_k^{bw} + \mu_k^{bw}(\mu_k^{bw})^T
\]

\[
E[\Delta P_k(\Delta P_{k-1})^T] = J_{k-1}V_k^{bw} + \mu_k^{bw}(\mu_{k-1})^T. \quad (3)
\]

With the statistical estimate of \(\{\Delta P_k\}\) in (3) and the measurement set sequence \((P_{S,k} - P_{S,k})\), EM algorithm can estimate the parameters using maximum-likelihood method over the complete-data log-likelihood function and obtain

\[
\hat{\mu}_0 = E[\Delta P_1], \quad V_0^{new} = E[\Delta P_1(\Delta P_1)^T] - E[\Delta P_1]E[\Delta P_1]^T,
\]

\[
A' = \left( \sum_{k=2}^{N} E[\Delta P_k(\Delta P_k)^T] \right)^{-1} \left( \sum_{k=2}^{N} E[\Delta P_{k-1}(\Delta P_{k-1})^T] \right).
\]

These new parameters are treated as \(\theta^{old}\) in a subsequent E-step and a new round of EM computation is started until the parameters converge. Once we obtain \(A\), we can use it to predict the system operator’s behavior.

B. Obtaining the conditional mean and variance

Once we obtain the matrix \(A\), as a byproduct we can also obtain the estimated \(\{\Delta P_{S,k}\}\). By using it, together with the sequence \(\{P_{S,k}\}\), we can obtain the conditional mean and variance from the following scheme (Figure 4 as an illustration): 1) discretize the scheduled power \(P_S\) into different levels. For instance, if the scheduled power of the \(i\)th generator has a range of \([P_{min}^{Si}, P_{max}^{Si}]\), then we can use \([P_{min}^{Si}, P_{S1}^{Si}], [P_{S1}^{Si}, P_{S2}^{Si}], \ldots, [P_{S8}^{Si}, P_{max}^{Si}]\) to represent different levels. 2) cluster the historical data into the nearest scheduled power level bin via nearest neighbor search. For instance, the data in time slots 1, 3, 5, and 6 in Figure 4 are grouped into one level. 3) obtain the statistical mean and variance in each bin, i.e. \([P_{S1,1}, P_{S1,2}]\). For instance, we can compute mean (0.2050) and the variance (0.0043) for the group of time slots 1, 3, 5, and 6 in the same bin. This information will be the input to the robust control in the next section.

![Fig. 4: System operator’s pattern learned from historical data.](image)

\[
\text{Fig. 4: System operator’s pattern learned from historical data.}
\]

Figure 5 uses the monthly data from five bus system described in Section II. This data set is generated every 5 minutes, resulting in 290 per day data point for each generator. Each data point is associated with two parameters: \(P_{S,i}\), the scheduled power, and \(\hat{P}_{S,i}\), the measured generated power. The x-coordinate is used to describe the time index in one hour. The left three figures show the scheduled power and the measured power generation. The right three figures show the learned pattern of the system operation by using the historical data given in Section II. Data shown in Figure 5 are obtained using historical data for two months. The learned predicted hour is Monday 9 am. This provides the needed information to the (I)SO, namely the expected mean and variance characterizing generator likely behavior. For instance, in the upper left figure at time index 1, when the scheduled generation of generator 1 is around 0.19, the system operator tends to approximately 0.056 per unit less power as described in the top right sub-figure. Such a behavior is with a confidence interval (0.056 − 0.048, 0.056 + 0.048), capturing 95% observed results.

IV. ADAPTIVE CONTROL OF NON-ZERO MEAN INTRA-RTD IMBALANCES USING ROBUST TWO-STAGE OPTIMIZATION

Conventional RTD is conducted once at the beginning of each RTD interval, which provides the generators with the scheduled generation output \(P_{S,0}\) for the group of time slots \(P_{S,0}\). It assumes that all generators follow the schedule exactly during the interval. However, the deviation \(\Delta P_S\) of actual generation \(P_S\) from the scheduled \(P_{S,0}\) creates intra-RTD supply-demand imbalance. On the other hand, it is shown in the previous section that the (I)SO can predict from historical data the region \(\hat{\Omega} = \{\Delta P_{S,min}, \Delta P_{S,max}\}\) of this deviation. To this end, a method is needed to utilize the predicted \(\hat{\Omega}\) to provide the (I)SO an optimal way to dispatch generators to prevent potential large intra-RTD imbalance, and to reduce the imbalance recovery cost. We propose an adaptive controller to compensate the likely intra-RTD imbalance, using two-stage robust optimization \([5]\).

A. Proposed Adaptive Controller

We assume that the actual generation can be measured at the beginning of each RTD interval. Thus, in each RTD interval,
the (I)SO adaptively controls the generators’ output in two stages: Stage 1: Before the beginning of the RTD interval, the (I)SO obtains schedules for both slow and fast generators, \( P_S \) and \( P_F \), taking into account the predicted region \( \hat{\Omega} \) of the slow generator deviation \( \Delta P_S \) and the corresponding recovery cost. Stage 2: Right at the beginning of the RTD interval, the (I)SO measures the deviation of slow generators \( \Delta P_S \), and adjusts fast generators by \( \Delta P_F \) to meet intra-RTD supply-demand balance. In the rest of the section, we first quantify the cost incurred by actions conducted by the (I)SO in stage 2, namely, recovery cost. Thus, optimal recovery strategy in stage 2 can be found to achieve minimum recovery cost. We further define the worst-case recovery cost, and explain how to optimally schedule generators in stage 1 considering the worst-case recovery cost.

B. Recovery Cost and Optimal Stage-2 Strategy

Once the (I)SO observes slow generators’ output deviation \( \Delta P_S\), it adjusts fast generator by \( \Delta P_F\) to meet the supply-demand balance, which incurs the cost of \( \Delta P_F^T Q \Delta P_F \), where \( Q \) is the weight matrix. Given stage-1 schedule \( P_S, P_F \) and slow generators’ deviation \( \Delta P_S \), the recovery cost \( R(P_S, P_F, \Delta P_S) \), is then defined as the cost incurred by optimal adjustment \( \Delta P_F^* \), i.e.,

\[
R(P_S, P_F, \Delta P_S) = \min_{\Delta P_F \in \Omega(P_S, P_F, \Delta P_S)} \Delta P_F^T Q \Delta P_F, \tag{5}
\]

where, \( \Omega(P_S, P_F, \Delta P_S) = \{ \Delta P_F \in \mathbb{R}^{n_F} | \sum_{i=1}^{n_S} (P_{S_i} + \Delta P_{S_i}) + \sum_{i=1}^{n_F} (P_{F_i} + \Delta P_{F_i}) = \sum_{i=1}^{n_D} P_{D_i} \} \tag{6} \]

\[
|F(P_S, P_F, \Delta P_S, \Delta P_F)| \leq F_{\text{max}} \tag{7} \]

where constraint (6) ensures intra-RTD supply-demand balance; (7) imposes transmission network flow limits. Note that we assume that fast generators have enough reserve to adjust their generation in response to the (I)SO.

As slow generators can deviate arbitrarily within the predicted region \( \hat{\Omega} \), there exists one deviation which will incur the highest recovery cost, which we call the worst-case recovery cost, denoted by \( R_{\text{wc}}(P_S, P_F; \hat{\Omega}) = \max_{\Delta P_S \in \hat{\Omega}} R(P_S, P_F, \Delta P_S) \), where \( \hat{\Omega} \) is the predicted region of deviation \( \Delta P_S \). Note that \( \hat{\Omega} \) can also depend on the generation schedule \( P_S \).

C. Finding Optimal Stage-1 Strategy

Before the beginning of each RTD interval, the (I)SO wants to find the generation schedule with minimum nominal generation cost \( C_S(P_S) + C_F(P_F) \) and worst-case recovery cost \( R_{\text{wc}}(P_S, P_F; \hat{\Omega}) \), where \( C_S(\cdot), C_F(\cdot) \) are cost functions for slow and fast generators, respectively. The optimal stage-1 strategy \( \{ P_S^*, P_F^* \} \) is obtained by solving

\[
\min_{P_S, P_F} C_S(P_S) + C_F(P_F) + R_{\text{wc}}(P_S, P_F; \hat{\Omega}) \tag{8}
\]

s.t. \[
\sum_{i=1}^{n_S} P_{S_i} + \sum_{i=1}^{n_F} P_{F_i} = \sum_{i=1}^{n_D} P_{D_i}, \tag{9}
\]

\[
|F(P_S, P_F)| \leq F_{\text{max}}, \tag{10}
\]

\[
P_S^{\text{min}} \leq P_S \leq P_S^{\text{max}}, P_F^{\text{min}} \leq P_F \leq P_F^{\text{max}} \tag{11}
\]

where (9) is scheduled-supply-demand balance constraint, (10) is scheduled transmission network flow limit constraint, and (11) enforces the generation limits for all generators.

D. Simulation Results

The simulation is conducted on the 5-bus system shown in Figure 1. The recovery cost weight matrix is \( Q = \text{diag}(2000, 2000) \). The predicted region \( \hat{\Omega} \) of deviation is obtained by methods shown in Section III. For illustration purposes, we post-process \( \hat{\Omega} \) by assuming \( \hat{\Omega}_i = [\alpha_i P_{S_i}, \pi_i P_{S_i}] \), i.e., the upper and lower limits of deviation \( \Delta P_{S_i} \) are proportional to the committed generation \( P_{S_i} \). As a result, the predicted regions of deviations for slow generators 1, 2, 3 are \( \hat{\Omega}_1 = [-0.3P_{S1}, -0.1P_{S1}] \), \( \hat{\Omega}_2 = [-0.2P_{S2}, -0.1P_{S2}] \), \( \hat{\Omega}_3 = [-0.05P_{S3}, 0.05P_{S3}] \).

Adaptive controller using two-stage optimization is applied to 1 hour to compare with conventional economic dispatch. Figure 6a show the stage-1 scheduled generation for 3 slow generators (\( P_S \)). According to the results, while conventional method dispatches the cheapest generator first, two-stage method takes into account their uncertainty, quantified by predicted region \( \hat{\Omega} \) of deviation. For example, generator 1 is the cheapest but has a larger uncertainty, which only provides 70% – 90% of its committed generation. It is then scheduled to generate a smaller amount of power, to reduce the recovery cost it may potentially incur in stage 2. Generator 3 is the most expensive among all slow generators, but it only deviates \( \pm 5\% \) of committed, which leads to lower recovery cost. To this end, it is scheduled to generate more in two-stage dispatch.

Figure 6b compares the recovery costs as results of two-stage dispatch and conventional dispatch. It is shown that the proposed method can significantly reduce the recovery cost, thus reduce the total cost.
synchronous generators connected to Buses 1, 2, and 3 have power generation offset from the pre-scheduled amount and the ramp rates of these generators are small. Besides, the intermittent resources connected to Bus 3 also inject persistent disturbances to the system. These disturbances are superposed and shown in Figure 7a. On the other hand, the synchronous generators connected to Buses 4 and 5 fully produce what is committed and their ramp rates are large. In Figure 8, we illustrate the effects of intra-RTD and E-AGC for comparison. For illustration purpose, the rotor speed of G1 is used as an example. It can be seen that the rotor speed varies largely with both inter-second continuous and 5-minute step changes.

The effectiveness of intra-RTD on reducing the disturbances can be observed by comparing Figures 7b and 7a. Figure 8b shows that the long-term step changes in the rotor speed responses are eliminated but the continuous variations still remain. This is because the intra-RTD only compensates in a predictive adaptive way the 5-minute step-change disturbances caused by the intentional failure of G1, G2, and G3 to produce what is committed; after intra-RTD is implemented, the near-zero-mean fast persistent disturbances caused by the intermittent resources and other very fast fluctuations still remain, which leads to the continuous rotor speed variations.

Then, we apply the E-AGC as the substitution of the intra-RTD. It can be seen in Figure 8c that both the step-change and continuous rotor speed variations are compensated by the E-AGC; however, there still exist high-magnitude spikes in the rotor speed response. This is because the E-AGC is only able to pick up the disturbances through corrective feedback control; besides, it is unable to respond instantaneously to the rotor speed deviations. Consequently, in response to those step-change disturbances, the E-AGC has to allow the existence of short-term spikes, which can be harmful to system equipment. Also, the intra-RTD requires less wear-and-tear, all else being equal. Finally, we combine the intra-RTD with the corrective E-AGC and implement the full control framework to the test system. It is seen (Fig.8d) that the rotor speed response is significantly smoother in comparison to all other three cases. The intra-RTD picks up most of the step-change disturbances caused by the conventional generators, and the E-AGC compensates the persistent and hard-to-predict disturbances.

VI. PRELIMINARY CONCLUSIONS AND OPEN QUESTIONS

One of the major conclusions in this paper is that a careful combination of predictions of slower resources (conventional power plants, responsive demand, clusters of EVs) and adaptive predictive intra-RTD balancing can go a long way toward enabling all resources to participate in real-time balancing and be paid/pay for this according to value. We conclude that the results are generally better than when using only E-AGC. Nearly all non-zero mean intra-RTD imbalance is best managed using a predictive adaptive approach like the one proposed in this paper. Only near zero-mean fast fluctuations must be managed using E-AGC. Open questions concern demonstration of the proposed approach using actual data for real-world power systems, and design of pricing mechanisms for providing economic incentives to the right power plants to participate in the most effective on-line power balancing.

ACKNOWLEDGMENTS

The first author greatly appreciates the discussions with Dr Petar Ristanović, Dr. Khaled Abdul-Rahman and Hani Alarian from California ISO regarding the need for predictive adaptive intra-RTD proposed in this paper. The authors look forward to future possible collaboration.

REFERENCES

[1] The claim is made based on the recent meeting of the first author at CaISO. This paper is largely motivated by the discussions at this meeting.