Model Predictive Control of Industrial Loads and Energy Storage for Demand Response

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***Abstract*—With the potential to enhance the power system's operational flexibility in a cost-effective way, demand response is gaining increased attention worldwide. Industrial loads such as cement crushing plants consume large amounts of electric energy and therefore are prime candidates for the provision of significant amounts of demand response. They have the capability to turn on/off an arbitrary number of their crushers thereby adjusting their electric power consumption. However, the change in power consumption by cement crushing plants and also other industrial loads are often not granular enough to provide valuable ancillary services such as regulation and load following. In this paper, we propose a coordination method based on model predictive control to overcome the granularity restriction with the help of an energy storage.**

***Index Terms*—Demand response, industrial loads, model predictive control, ARMA prediction, regulation, load following.**

I. Introduction

Renewable generation resources such as wind turbines and solar panels are expected to be widely deployed in the future to enable a sustainable energy future. However, the intermittent and uncertain nature of power output from these renewable resources imposes challenges on power system operation, which requires large amounts of balancing resources to enhance the operational flexibility of the grid. According to the Federal Energy Regulatory Commission, "effective demand response can help reduce electric price volatility, mitigate generation market power, and enhance reliability" [1]. Demand response is gaining increased popularity all over the world, as it demonstrates potentials to enhance the power system's operational flexibility in a cost-effective way [2]–[5]. Moreover, demand response has been one of the key components in the Smart Grid R&D program, as stated by the US Department of Energy: "One of the goals of the Smart Grid R&D Program is to develop grid modernization technologies, tools, and techniques for demand response" [6]. In recent years, there have emerged a number of studies and projects on demand response, provided by residential, commercial, or industrial loads, e.g. by electric vehicles [7], residential areas [8]–[10], buildings [11], aluminum smelters [12], [13], air separation units [14], as well as steel plants [15], [16].

Within the realm of demand response, industrial loads have the following advantages [17], [18]: most industrial loads have already installed the infrastructures for control, measurement, and communications which are necessary for demand response; the adjustments of the power consumption from many industrial loads can be very large, fast, and accurate; the industrial loads are also strongly motivated to participate in demand response programs even at the cost of increasing their operation complexity, as making profits is their primary concern. Industrial loads that can support the power system operation through demand response include aluminum smelting pots, steel melting furnaces, fans, freezers, pumps, mills, crushers, etc. The industrial demand response resources are not only participating in the energy markets through programs like load shifting, they are also actively providing ancillary services such as spinning reserve, load following, and regulation. For instance, in previous work we have studied the regulation provision and load following by aluminum smelters [12], developed an offering strategy for spinning reserve by aluminum smelters [13], and use a resource-task network framework to enable the steel plant scheduling with spinning reserve provision [15].

Different from spinning reserve which only involves the reduction of power consumption, regulation and load following require a much faster response of power change, both up and down, and hence are much more valuable in the ancillary service markets. Lots of industrial loads are able to provide very fast change of power in both directions, qualifying them for regulation and load following. For example, the crushers or mills in the cement industry can be switched on and off very rapidly [19], [20]. However, most of these industrial loads can only provide power changes in a discrete manner, e.g. the power change is several MWs at a time. This coarse granularity hinders those industrial loads from providing the most valuable ancillary services, as the regulation and load following in the current electricity markets require a continuous change of power. Consequently, these balancing resources with fast consumption changing capability are not utilized to the full extent.

In this paper, we intend to overcome the granularity restriction for those industrial loads discussed above. We propose a coordination framework in which the industrial loads provide the regulation or load following services with the help from an on-site energy storage: the industrial loads provide a large but discrete power change which constitutes as the main body for the service, while the energy storage provides a fine and continuous power change which ensures that the combination of the two accurately follows the desired power signal. These two parts are coordinated by a model predictive control (MPC) approach which incorporates the prediction of the upcoming signals of the services into the decision making. As seen in

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the case study, the combination of the industrial loads and the energy storage is able to accurately follow the regulation or load following command in a very wide range.

The key contribution of this work is the proposed coordination method for providing ancillary services such as regulation and load following by a combination of a storage device and an industrial plant capable of adjusting its power consumption in large discrete steps. We demonstrate that the whole is greater than the sum of its parts. The remaining of the paper is organized as follows: Section II describes the considered problem. Section III presents the coordination method by MPC, in which the prediction method is introduced in Section III-A and the optimization at each MPC step is explained in Section III-B. The case study for the cement crushers and energy storage is discussed in Section IV to demonstrate the effectiveness of the proposed approaches, based on which the conclusions are drawn in Section V.

II. Problem Statement

A variety of industrial loads can be switched on and off very rapidly, which enables them to change the power consumption rate fast and frequently, e.g. the crushers (mills) in the cement crushing industry [19] and the crushers in the thermal mechanical paper & pulp industry [21]. In this paper, we want to investigate and provide the mechanisms to use these industrial loads for the provision of regulation service. However, the proposed method can also be employed to enable load following. For simplicity, we assume there are n machines which can be switched on and off rapidly, and each machine has a power consumption rate of ρ MW. Note that in practice the power consumption rates for different machines may not be the same, yet the proposed method can be easily extended to consider this deviation from our assumption.

The regulation signal of PJM (currently the largest competitive wholesale electricity market in the US) is published in [22], in which the RegD dynamic regulation signal is designed for fast-responding resources. We will use this RegD signal for our study. The accurate prediction of the regulation signal is impossible over a long time period, e.g. several minutes. However, predictions with reasonable accuracy for a horizon of around 1 minute are possible by using autoregressive-moving-average (ARMA) models. As demonstrated later, this prediction is good enough for the coordination of the industrial loads and the energy storage. The regulation signal is in per unit value and it ranges between -1.0 and 1.0. This signal multiplied by the regulation capacity R MW plus the regulation baseline B MW is the regulation command for the industrial plant, i.e. the targeted power consumption rate in MW.

The industrial loads are switched on/off or adjusted to follow the regulation command with the support of an on-site energy storage. It has been demonstrated that stand alone storage has significant potentials to support the power system operation [23], [24], whereas in this paper the flexible charging power of the storage helps the industrial loads to overcome the granularity restriction. We assume that the storage has a maximum energy capacity of E MWh and its charging power

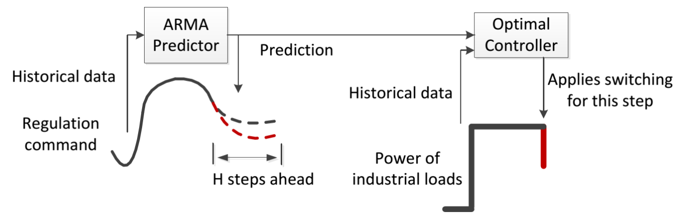

Fig. 1. MPC coordination framework.

is bounded by $-P$ and P MW. To simplify the problem, we further assume that there is no energy loss associated with the charging and discharging processes. Note that the energy loss can be considered easily by extending the formulations. The industrial loads and the energy storage are coordinated by the MPC method, which is presented in the following section.

III. Coordination by Model Predictive Control

The coordination framework is illustrated in Fig. 1. At each step t, the ARMA predictor outputs the regulation prediction for the next H steps, based on historical regulation commands; then the optimal controller optimizes over the number of active machines x_i and the storage charging power y_i for each time $i = t, \cdots, t+H$ in the MPC horizon, based on the regulation prediction and previous operation record of the machines; after obtaining the optimization results, only the optimal decisions for the current time step t is applied to the industrial loads and the energy storage.

A. Prediction

We have trained different ARMA models by the Time Series Analysis package in Python (*statsmodels.tsa*). For different training data sets [22], the ARMA(2,1) model resulted in the best performance, in terms of Akaike information criterion (AIC) scores. The ARMA (2,1) model is described by:

$$\omega_t = \phi_1 \omega_{t-1} + \phi_2 \omega_{t-2} + \theta_1 \epsilon_{t-1} + \epsilon_t$$

in which ω_t stands for the regulation signal, ϵ_t stands for the white noise. The auto-regressive parameters ϕ_1, ϕ_2 and moving-average parameters θ_1 are trained and obtained by the Python package *statsmodels.tsa*. The regulation prediction mean squared errors by ARMA(2,1) for different prediction horizons are plotted in Fig. 2 and compared to the Persistence Model and the Mean Prediction approach. The Persistence Model uses the latest available observation as prediction and the Mean Prediction uses the average from all available observations as prediction. According to Fig. 2, the ARMA(2,1) model results in a good performance up to horizons of around 1 minute by ARMA(2,1). The Python implementation for the prediction is available online[1].

B. Optimal Control

The objective of the optimal control is to provide high quality regulation service at low cost. The decision variables for

[1] https://github.com/xxxzhang/Reg

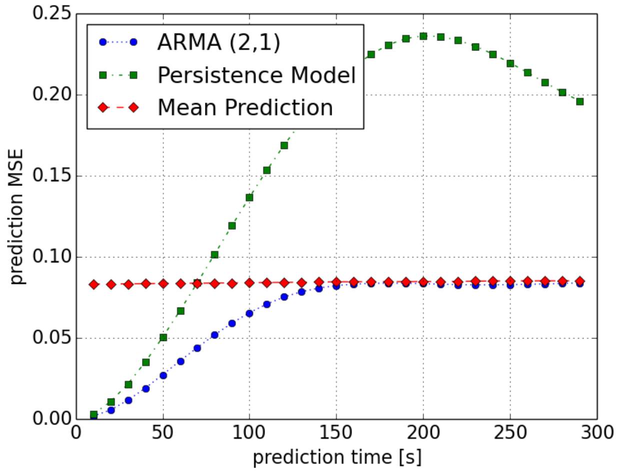

Fig. 2. Prediction mean squared errors.

the optimal control are the number of active machines and the charging power for the storage. In this paper, we assume that the regulation capacity and the regulation baseline are fixed in advance and they are denoted as R (MW) and B (MW), respectively; how to optimally choose these values is part of future research. Note that the average power consumption of the industrial machines is therefore B MW, as the regulation signal is balanced, i.e. the integral over time is zero; this indicates that the plant throughput, which is proportional to the energy (MWh) it consumes, is close to the base load, as the energy level in the storage changes very little. The optimization formulations for the optimal control are stated as follows.

1) Objective: In the optimization objective, we penalize the regulation violation v_i, the number of machines switching action s_i, and the deviation d of the final storage energy level from the targeted level, as in:

$$\text{minimize} \quad \sum_{i \in H} (\alpha v_i + \beta s_i) + \gamma d \tag{1}$$

in which α, β, γ are the penalty parameters. Different values of the penalty parameters indicate different preferences for the regulation provision. Details of the impact of these parameters are discussed in the case study.

2) Regulation Violation: The regulation signal prediction for step i within the optimization horizon is denoted as $\widehat{\omega}_{t+i}$. According to the regulation prediction, the regulation violation v_{t+i} at the i-th step is defined as:

$$v_{t+i} \geq |B + R\widehat{\omega}_{t+i} - P_m x_{t+i} - y_{t+i}| \quad \forall i \in H \tag{2}$$

in which the first two terms on the right side correspond to the regulation command and the last two terms correspond to the plant power consumption rate. Since we penalize v_{t+i} in the objective function, the above constraint can be formulated as two linear inequality constraints.

3) Machine Switching: Too much switching of the machines potentially increases degradation and may even damage the machines; that is why we penalize the number of switch actions in the objective function. The number of switch actions s_{t+i} at the i-th step is defined as:

$$s_i \geq |x_{t+i} - x_{t+i-1}| \quad \forall i \in H \tag{3}$$

in which the right side represents the change in the number of active machines between time steps.

4) Storage Level Deviation: Another objective is to control the final energy level in the storage for each MPC horizon. Otherwise, if the energy level is near its full capacity, then there is little room for the storage to contribute to the provision of regulation. This deviation is defined as

$$d \geq |e_{t+H} - \overline{e}| \tag{4}$$

in which $\overline{e}$ is the targeted storage level. We usually set $\overline{e}$ equal to 50% of its energy capacity.

5) Storage Energy Balance: The energy balance for the storage describes the relationship between stored energy and its charging power, as given by:

$$e_{t+i} - e_{t+i-1} = y_{t+i}\delta \quad \forall h \in H \tag{5}$$

where δ is the length of one time step. In addition, the energy in the storage is constrained by the storage capacity.

6) Switching Limitation: In practice, the industrial machines cannot be switched on/off without causing inconvenience. For example, the machines cannot be switched too frequently, otherwise the machines could get damaged. Hence, we restrict the number of switch actions to be no more than $\overline{s}$ for every successive L steps (typically, $L > H$) for each MPC step t and each time i in the MPC horizon, as given by:

$$\sum_{j=t+i-L}^{t-1} \widetilde{s}_j + \sum_{j=t}^{t+i} s_j \leq \overline{s} \quad \forall i \in H \tag{6}$$

in which the first term corresponds to the summation of switch actions that already took place before i, and the second term stands for the possible number of switch actions that may take place from i to the end of this MPC horizon. Note that the above constraint applies to each step i within the MPC time horizon, as we require the switching to not violate the bound on number of switchings for every successive L steps. Consider an example where H is 10 steps and L corresponds to 100 steps, if there are $\overline{s}$ times of switching between t-100 and t-90, then the first 10 steps within this MPC horizon cannot allow for any switching. Other constraints on switching limitation can be considered in a similar way, e.g. the minimum energy consumption requirement of the machines for successive time durations.

7) Variable Ranges: The decision variables can take values within the following bounds:

$$x_{t+i} \in \{0, 1, ..., n\} \text{ and } -P_s \leq y_{t+i} \leq P_s \quad \forall i \in H \tag{7}$$

in which x_{t+i} is an integer variable while y_{t+i} is a continuous variable.

To sum up, the MPC recedes forward and at each time step t, it first predicts the upcoming regulation signals, then optimizes (1) subject to constraints (2)-(7), but only applies the optimal decisions at time step t. The resulting optimization problem is a mixed integer linear programming problem, which can be solved by CPLEX very quickly as the problem size is small.

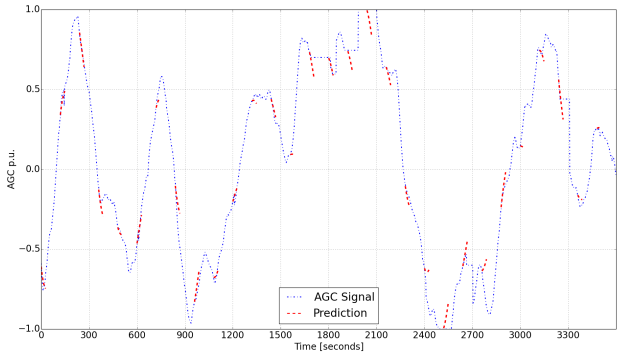

Fig. 3. Regulation signal (AGC) over one hour and its prediction.

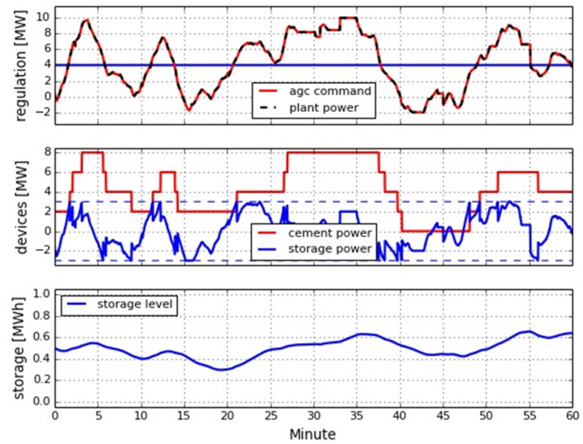

Fig. 4. MPC simulation results.

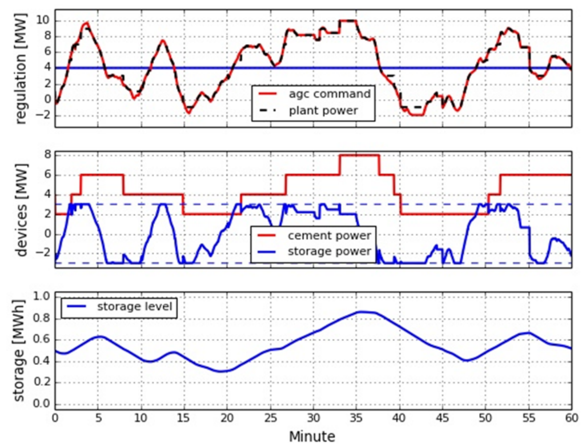

Fig. 5. Simulation results with increased penalty on switch actions.

IV. Case Study

A. Parameters

For the case study, we consider a cement plant with $n = 4$ crushing machines which can be switched on and off rapidly. The power consumption rate of each machine is $P_m = 2$ MW when it is on. The on-site energy storage has $E = 1$ MWh energy capacity and its maximum charging/discharging power is $P_s = 3$ MW [25]. In the following simulations, the cement plant provides $R = 6$ MW regulation at a baseline of $B = 4$ MW. In other words, the regulation command ranges between -2 MW and 10 MW. Note that the range of the regulation command is 12 MW, which is much higher than that of the energy storage. The one hour regulation signal for the simulation is plotted in Fig 3, together with the ARMA(2,1) prediction at a few distinct time instances. The length of the time step is $\delta = 2$ seconds.

B. Simulation Results

The MPC simulation results over the hour are plotted in Fig. 4, in which the prediction horizon is $H = 15$ steps, the penalties α, β, γ are all taken as 10, the targeted final energy is $\bar{e} = 0.5$ MWh, and we require the maximum number of switch actions to be $\bar{s} = 10$ times for every successive 5 minutes, i.e. $L = 150$ steps. According to the simulation in Fig. 4, the integral of regulation violation over the hour is only 0.01 MWh, the total number of switch actions is 21 times, and the storage energy level at the end of the hour is 0.6 MWh, i.e the energy deviation is 0.1 MWh. In the second plot in Fig. 4, the dashed lines are the bounds for the charging/discharging power of the storage. The simulation results demonstrate that the coordination method proposed in this paper is able to utilize the advantages from both the industrial loads and the energy storage, and provides high-quality regulation service to support the power system operation.

The impacts of the penalties are investigated by simulations with different penalty values. First of all, if we increase the penalty on switch actions β, the total number of switch actions is expected to decrease. For example, increasing β to 200 while keeping all other parameters the same as before yields to the simulation results in Fig. 5, in which the total number of switches decreases to 12 times but the regulation violation increases to 0.12 MWh. Secondly, if we increase the penalty on the energy level deviation γ, then we can do better at stabilizing the energy level in the storage. For instance, the simulation results for increasing γ to 1000 while keeping all other parameters unchanged at 10 are displayed in Fig. 6, in which the energy level in the storage is very stable, however, there are as many as 34 switching actions. Thirdly, if we impose a stronger switch limitation constraint, e.g. requiring the maximum number of switches to be 4 for every successive 5 minutes, then the switch frequency will decrease, as demonstrated by the simulation results in Fig. 7. However, there is more regulation violation and the storage energy level varies dramatically.

In practice, we suggest to the plant operators to choose their own penalties according to their preferences. For example, in an electricity market where the regulation quality is highly valued, a higher regulation violation penalty α is recommended; meanwhile, if switching the machines is very expensive, then the operator should use a large switching action penalty β.

V. Conclusion

The key contribution of this work is the proposed coordination method for providing the most valuable ancillary services such as regulation and load following by the combination of the industrial loads, which can adjust their power consumption only in large discrete steps, and the energy storage, which provides the more granular power adjustments.

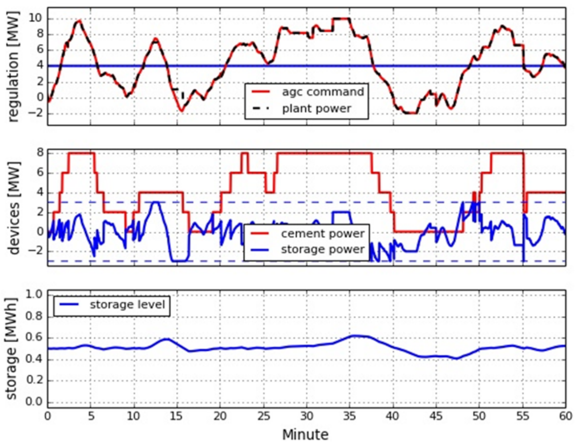

Fig. 6. Simulation results with increased penalty on energy deviation.

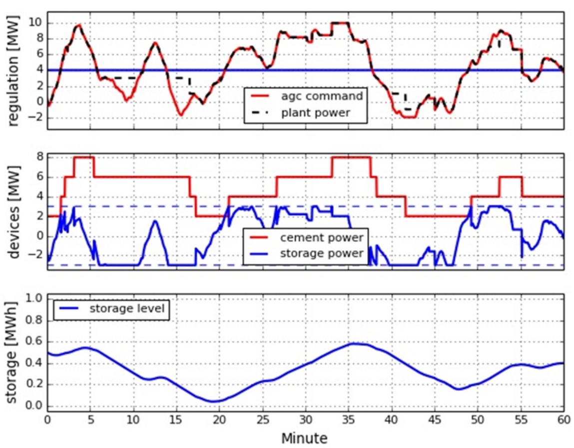

Fig. 7. Simulation results with stronger switching limitation constraint.

Thanks to the coordination method proposed in this paper, the industrial loads have more options in supporting the power system operation through demand response. The industrial loads are able to overcome the granularity restriction and provide regulation or load following ancillary services, with the help of an on-site energy storage. The power change from the industrial loads serve as the main contributor in the service, while the charging power from the storage is responsible for eliminating the mismatches. Note that the method proposed in this paper applies to a variety of industries, e.g. cement crushing, paper milling, and steel melting, and applies to both load following and regulation service. The proposed framework also has other potential applications outside of demand response, e.g. the coordination among fast and slow generators and energy storage.

Additional future work includes how to optimally decide the regulation capacity and baseline for the combination of industrial loads and energy storage, and how to schedule the entire industrial plant such that providing regulation will not interrupt the processing flows within the plant. Some practical concerns also need to be addressed such as the charging/discharging loss in the energy storage and the mileage compensation in providing the regulation or load following service. Besides, the method proposed here intends to provides a solution to the problem that the current electricity markets cannot fully utilize the loads with fast switching capabilities due to their restrictions on granularity.

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