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Multi-rate modeling and economic model predictive control of the electric arc furnace

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ABSTRACT

In this manuscript, we consider the problem of multi-rate modeling and economic model predictive control (EMPC) of electric arc furnaces (EAF), which are widely used in the steel industry to produce molten steel from scrap metal. The two main challenges that we address are the multi-rate nature of the measurement availability, and the requirement to achieve final product of a desired characteristic, while minimizing the operation cost. To this end, multi-rate models are identified that include predictions for both the infrequently and frequently measured process variables. The models comprise local linear models and an appropriate weighting scheme to capture the nonlinear nature of the EAF. The resulting model is integrated into a two-tiered predictive controller that enables achieving the target end-point while minimizing the associated cost. The EMPC is implemented on the EAF process and the closed-loop simulation results subject to the limited availability of process measurements and noise illustrate the improvement in economic performance over existing trajectory-tracking approaches.

1. Introduction

Electric arc furnaces (EAF) play a prominent role in the steel industry and are widely used for recycling scrap metal. Operated primarily as batch processes (a batch is referred to as a heat), EAFs melt the scrap and adjust the chemical composition of the molten metal to obtain steel of the desired product grade. The required melting of steel scrap results in a highly energy intensive process, necessitating efficient operation. Given that the feed to the EAF, from recycled steel, comes from diverse sources with obscure compositions that vary significantly, efficient operation can only be achieved via an online measurement and feedback control strategy. Closed-loop control of the EAF, however, presents a challenging problem due to the lack of on-line measurements of key process variables. This complicates both the model development and control implementation steps.

One approach to modeling and control of the EAF process in particular [1–5], and batch processes [6,7] in general, is to develop first-principles/mechanistic models, and use them for the purpose of optimization. Note that while a first-principles model provides excellent predictive capabilities when sufficient measurements are available to uniquely estimate the associated parameters, the resultant optimization problem is often quite computationally complex, and difficult to solve and implement in real-time. To address these challenges, recent results have exploited the structure of the optimization problem to identify the shape of the optimal constraints, which can then be parameterized and readily updated online [8,9]. More recently, the concept of reachability regions is used to implement model predictive control strategies where the controller, instead of trying to drive the process to the desired end-point at all computation times, guides the process through the reachability regions (computed off-line) [10,11]. Another effort to shift the computational effort to an offline step includes design of explicit model predictive control involving multi-parametric programming, where the state of the system is represented as a vector of parameters so that the optimal solution for all possible realizations of the state vector can be pre-computed as explicit functions [12,13]. While these approaches mitigate the online computation aspect of the problem, the problem of developing and implementing a first-principles model-based controller remains a challenging task.

The first-principles model-based control approaches typically require initialization of the nonlinear process models using an effective state estimator so that the necessary feedback control actions can be applied. However, inferring the states of the EAF process based on the available process data is not a trivial task due to the lack of frequent on-line measurements. Furthermore, the fast convergence of the state estimator from initialization errors and

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the ability to handle measurement noise are critical, and may not be achieved with the limited, infrequent sampling rate for the EAF process variables.

One approach to address these practical problems is through use of simpler, data-driven model-based controller. However, in developing data-driven models, the identification experiments traditionally utilized to build empirical models, while suitable for identification at steady-state operating conditions, are often too expensive to justify for batch systems. In particular, identification techniques that require the implementation of a pseudo-random binary sequence (PRBS) on the process, may result in off-spec product, and thus wastage of expensive batches, making them economically infeasible. Thus, for batch systems, the available plant data is essentially limited to the historical databases comprised of prior batches (possibly augmented with a limited number of identification experiments). Furthermore, the process dynamics of batch systems are typically highly nonlinear, and they are not operated around an equilibrium point, thus making conventional system identification approaches, where a single linear model is identified, ill-suited for identifying an accurate dynamic model.

One general strategy to describe nonlinear behavior while retaining the simplicity of linear models is to partition/cluster the training data into a number of different regions, identify local linear models for each region, and combine them with appropriate weights in an attempt to describe the global nonlinear behavior. This idea has been formalized in piece-wise affine (PWA) [14], Takagi, Sugeno, and Kang (TSK) [15], and operating-regime based [16] modeling. Recently, a new multi-model approach, specific to batch processes, was proposed that unifies the concepts of dynamic modeling, latent variable regression techniques, fuzzy *c*-means clustering, and multiple local linear models in an integrated framework to capture the nonlinear nature of batch data [17]. The key delineating aspects of the work are the integration of the clustering algorithm used to partition the training data, the use of latent variable tools to estimate the model parameters, and the utilization of a generalized continuous weighting function that is entirely data dependent and does not require precise process knowledge [17]. Additionally, the resulting model is readily applicable in an online optimization framework [18]. The model development in these approaches, however, assumes the process measurements to be available at the same sampling rate, motivating the need to generalize these results for the case of the EAF process, where measurements are available at different sampling rates.

Regardless of the nature of the model used, the control problem can benefit from utilizing notions of economic control recently proposed for continuous processes [19–23]. The key idea in these developments is that the controller determines the set-point internally to satisfy the prescribed economic objective, and requires a rigorous analysis to ensure stability is preserved. In contrast, the batch control problem requires driving the process to a target that is often not a steady-state, but is the desired end-point. Online control of EAF processes therefore stands to gain from incorporation of economic considerations in the control implementation. Motivated by the above considerations, this work addresses the problem of economic model predictive control (EMPC) of the electric arc furnace using data-driven models. To this end, we first review the electric arc furnace process, and present a first-principles model that we utilize as a test-bed to implement and validate the proposed approach. We also review the existing data-driven multi-model approach for batch process control in Section 2. Subsequently, multi-rate models are proposed in Section 3.1 that incorporate infrequent and frequent measurements to improve the predictions of the process variables. In Section 3.2, multi-rate models for the EAF process are computed. In Section 4.1 a two-tiered economic MPC is developed. In the first tier, the best achievable product (in terms of meeting product specifications) is determined by penalizing the deviation of the end-point variables from the desired target, while accounting for the input constraints in the optimization problem. Then, in the second layer, the optimal inputs are computed where the best achievable end-point (computed using the first layer) is imposed as a constraint, with economic requirements specified in the objective function. The proposed two-tiered economic MPC method and the closed-loop simulation results demonstrating its effectiveness are presented in Section 4.2. The conclusions of this work are summarized in Section 5.

2. Preliminaries

A description of the electric arc furnace process is provided below, followed by the description of the test-bed model, and the aspects of the simulation designed to replicate practical application issues. Then a review of an existing data-driven multi-model approach for batch process control is presented.

2.1. Electric arc furnace process

The EAF is a batch process that involves a series of distinct operating phases that include the initial charging of the batch, followed by preheating, melting and tapping of the furnace. The scrap charge is generally comprised of a variety of sources selected based on a number of factors such as the availability of each scrap source and the desired product grade. Typically, two or three loads of scrap are charged in each batch depending on the bulk density of the scrap and the volume of the furnace. The furnace charge may also be supplemented with some direct reduced iron (DRI) or pig iron for chemical balance and to improve production yields. Once the batch is charged, the EAF is preheated through natural gas combustion to raise the temperature of the steel. Subsequent to preheating, electrodes are lowered into the furnace and the electric power is turned on to an intermediate voltage while the electrodes bore into the scrap. The voltage is increased once a sufficient amount of molten steel is formed at the base of the arc and the electrodes are submerged into the melt to avoid damage to the furnace walls. During the initial stages of the meltdown, a high voltage is selected that allows for more energy to be transferred to the surrounding scrap. As the batch approaches completion, a lower voltage arc is preferred to avoid damage to the exposed furnace walls. Moreover, slag is foamed during the EAF operation by lancing carbon and oxygen to form carbon monoxide gas that bubbles through the slag layer. The foaming slag cloaks the arc, thereby protecting the furnace walls from arc radiation and improving the energy efficiency. During the batch operation, impurities such as phosphorus, sulfur, aluminum, silicon, manganese and carbon are removed from the steel as they react with oxygen and float into the slag. After a predefined batch duration, the temperature and carbon content of the steel are measured to determine whether further inputs are needed to reach the desired end-point specifications [4,5]. Once the desired steel composition and temperature are obtained, the vessel is tapped and the molten steel is poured into a ladle for transport to the downstream units for further processing.

In this work, we focus on the melting process (see Fig. 1 for a schematic of an EAF during the melting stage). To this end, we utilize a first-principles model as a test-bed [2,24]. The model describes the melting process by using a total of 14 state variables and six manipulated variables. The model parameters were estimated using operating data from an industrial EAF [24]. While the model is focused on the melting process, and does not capture all the details of the EAF process, it is sufficiently detailed and validated through real plant data, making it an excellent candidate to adapt and utilize as a test-bed to implement and evaluate the proposed approach.