Advanced Temperature Control Applied on An Industrial Box Furnace

The current control system of an industrial box furnace usually uses a proportional-integral-derivative (PID) controller. Typically, this control system requires on-site tuning and specific heuristic knowledge, such that the furnace can have acceptable performance but not optimal. However, by using a proper model in the operating range of the furnace from the designing phase, it can be designed a more efficient control system capable to reach better performance in this industrial process. In this sense, the main objective of this paper is the design and validation of an advanced control strategy in the early design stage of an industrial box furnace. The goals are to decrease the controller tuning time during the furnace commissioning process, improve the furnace performance with respect to classical industrial controllers, and decrease the system energy expenses. Thus, a comparative analysis in a simulated environment has been carried out between the performance of a PID controller by its typical industrial use, a model predictive control (MPC) due to the optimal results in similar industrial processes, and a virtual reference feedback tuning (VRFT) control by its feasibility of implementation. Results show that the advanced MPC and VRFT controllers are more efficient in the used fuel/gas than the PID. MPC shows the best balance between performance and actuation, it improves the control performance up to 87.2% with respect to the VRFT controller. [DOI: 10.1115/1.4052020]

1 Introduction

Advanced process control allows the generation of economic profits and high-quality products in the industry. Typically, the box furnaces are controlled by hybrid systems (industrial sequential control + automatic regulatory control) where the programmable logic controllers supervise proportional integral derivative (PID) controllers for continuous operations. The main limitation of these controllers is their application in narrow operating domains, and their performance is not guaranteed when the furnace operating condition is time-varying. In these circumstances, usually, the PID control system must be able to be easy of tuning for several required operating conditions.

Typically, a box furnace is designed to perform a particular thermodynamic process under an open-loop control system. The profile of the fuel energy power is the model input whereas the furnace temperature is the output; the energy balance is based on a dimensional thermodynamic model. Most of the time, the furnace design is done for specific domain operations, so it results in a customized product. Its open-loop control performance can be simulated through a steady-state mathematical model or even with complex models using computational fluid dynamics (CFD).

Once the furnace thermodynamic model has been validated by CFD or steady-state mathematical model, the need is the design of an automatic controller capable to exploit the full thermal capability of the furnace or optimize its performance. However, there are technical challenges to achieve this controller capability. First, the development of a model to include it into the synthesis of a controller is a complex task since it is necessary to design the experiments in the entire operation domain of the furnace and look for a parametric structure that can describe properly the input–output behavior. Second, it is not easy to handle the combination of measured experimental data and empirical data from design as inputs for the controller synthesis of the furnace. Empirical data correspond to the physical dimensions, materials used in the fabrication, thermodynamic properties, load features, etc.

In industrial practice, the PID controller tuning is a heuristic process dependent on the control engineer, which usually is based on a trial and error iterative procedure. Finally, the closed-loop control performance of the furnace can be acceptable but not optimal. Some advanced control approaches focused on overcoming the PID performance in industrial furnaces have been proposed. For instance, the sliding mode control in Ref. [1] allows a soft control action reducing the system energy expenses, the model-predictive control presented in Ref. [2] also reduces the fuel consumption, in Ref. [3] a fuzzy controller provides better stability and robust performance under load variations, or more recently a self-adapting predictive control technique is used in Ref. [4] to outperform the PID control action in stability and fuel consumption particularly in the transient furnace operating conditions.

Although the aforementioned advanced control strategies overcome the PID controller results, they do not introduce designing parameters in their synthesis, such that the operating control analysis is not part of the concurrent prototyping process of an industrial kiln. In this way, the contribution of this paper is aligned with one of the main needing of the manufacturing industry of box furnaces, such as the design and implementation of an optimal control algorithm in the early design stage of the furnace, achieving three goals: (1) to decrease the controller tuning time during furnace commissioning process, (2) to improve the closed-loop control performance of the furnace (quality and volume of production), and (3) to decrease the system energy expenses. If the temperature control system performance of the furnace can be carried out using the physical-design thermodynamic model of the kiln, the aforementioned goals will be reached allowing to decrease the time-to-market manufacturing and guarantee on-site customer satisfaction. This work explores two different controllers and compares their performance to a PID controller in an industrial box furnace during its early design stage. A zero-dimensional thermodynamic
model is transformed into a proper model structure for the controllers’ synthesis. The key element to select a proper control system for this kind of application is to find a strategy capable to simultaneously reduce the energy consumption and minimize the deviations of the instantaneous load temperature from prescribed values during a heat-treatment process. In this sense, the general approach of this paper states a comparison between two control strategies able to handle the energy consumption and the reference trajectory tracking (desired temperature profile). According to similar thermodynamic applications, this analysis will be carried out in two of the following control strategies: sliding-mode control [1], fuzzy control [3], model predictive control [2,5,6], feed-forward techniques [4], decoupling control [7], and model-free control [8].

The paper is organized as follows: Sec. 2 discusses the typical controller approaches that have been studied in similar thermodynamic processes in a box furnace and highlights the selection criteria for the considered controllers in this study. The industrial box furnace used as a test-bed is described in Sec. 3. Section 4 describes the main features of the selected controllers and presents their general procedure of synthesis. Simulation results of the closed-loop control systems, as well their comparison under the same operating conditions, are discussed in Sec. 5. Finally, Sec. 6 concludes the paper.

2 Control Systems for Thermodynamic Processes

The advanced automatic control of industrial thermodynamic processes requires adequate control strategies for their wide operating range. Usually, these systems in their whole behavior are non-linear by nature. When a classical linear PID controller is considered as the main control system of the thermodynamic process, it is not possible to exploit the full actuation capability of the system. On the other hand, in general, advanced model-based controllers allow estimating the next states of the process to make more adaptive their operation. The model predictive control (MPC) strategy is the most used in the industry for the transformation processes [5,9–13]. The use of observers for those unmeasured process variables can solve instrumentation constraints [14]. Fuzzy control techniques are widely used with high success due to their easy implementation and commercial availability [15,16] but they need of using field engineering specialization. Recently, an interesting solution for controlling a nonlinear process is with the use of gain scheduling techniques, such as the recently developed linear parameter-varying control technique [17–20], but scarcely validated in industrial environments.

The temperature control in furnaces, particularly for walking beam furnaces, has been approached by different control techniques. The main results of the State-of-the-Art show that the MPC, sliding mode control (SMC), feed-forward control, and robust control techniques are the main approaches to solve the performance challenge in heat treatment with these devices. The SMC approach is the most used since 20 years ago, and more recently, Fuzzy control has been very popular in research papers. However, applied control research on industrial box furnace heat systems shows few experimental results.

2.1 State-of-the-Art: Control Systems in Furnaces. A bilinear self-tuning controller is applied to a non-linear model of an industrial heat treatment furnace in Goodhart et al. [21]. The control strategy is based on an extended pole-placement technique, whose effectiveness can be measured on the energy usage, maintenance, and wear on actuators; also, it considers penalty costs due to large deviations from the set-point. The application of SMC in an industrial furnace, in comparison with a sophisticated commercial PID controller, can be reviewed in Edwards and Spurgeon [1]; the nonlinear nature of the SMC allows improving the results of PID controller in a wider operating range. On the other hand, the control approach based on fuzzy logic has become a good choice for controlling industrial heat treatment furnaces [3,22]; due to their simplicity, these control approaches can be implemented with success in commercial box furnaces enhancing the qualification rate of the products from 92% to 98%, [23]. Nevertheless, as aforementioned facts, the most used model-based control strategy in industrial furnaces is the MPC. There are some industrial electronic boards capable to implement MPC control strategies when an accurate furnace model is available. For instance, the primary energy consumption in an industrial slab reheating furnace has reduced 9.6% with the implementation of a nonlinear MPC [6]. An enhanced MPC using a new state-space model structure for temperature control of an industrial coke furnace is proposed in Zhang et al. [24]. Recently, model-based control approaches have been also proposed by considering the zone method to decouple the actuation in different heating zones. In Ref. [7], internal model controllers, whose decoupling is based on the small-gain theorem, improve the sensitivity of system response and increase control precision with high robustness. It has been proved in Hu et al. [4] that a zone model with a self-adapting predictive control scheme outperforms the existing PID control scheme used for furnace control in terms of stability and fuel consumption (fuel saving of about 6%). Indeed, a self-adapt PID controller implementation could control the temperature of the furnace for several zones if a supervisory control system based on a prediction system performance is applied [25]. For a successful control implementation in a heat treatment furnace [26], the MPC must be synthesized from a good accuracy furnace model. In this sense, it is possible to improve the model accuracy if the data collection is done with several experiments and proper signals devised specifically to improve the model identification. On the other hand, it is a common experience in industrial control design that a mathematical description of the plant to be controlled is not available and that undertaking a modeling study is too costly and/or time-consuming. In these cases, one would like to come up with a controller tuned directly from measurements coming from the plant without going through a modeling phase. The virtual reference feedback tuning (VRFT) control algorithm permits tuning a controller within a specified class on the basis of a single set of input/output data collected from an experiment on the plant. This characteristic allows the consideration of a VRFT-based controller as a feasible option since the temperature processes in heating furnaces are very slow and the modeling phase could turn critical due to industrial timing [8]. The VRFT control algorithm has been implemented in several industrial processes with interesting results: with reactor temperature plant control [27], vehicle dynamics [28], boiler plant [29], twin-rotor aerodynamic system [30], braking control systems [31], self-balancing industrial manual manipulator [32], etc.

In summary, the literature review shows that a common practice is the use of PID controllers for the temperature control in furnaces due to theirs practical implementation aspects [1,3,23,25]. However, the MPC controller appears as a feasible solution with a more complex implementation but with a higher process quality control [4,24,26]. And recently, it has been proved that the VRFT control algorithm is a good solution for industrial processes with slow transient dynamics such as the temperature control in a box furnace. In this sense, three controllers have been chosen for this study: a PID controller since it is the typical one chosen by manufacturing companies of industrial furnaces [25], an MPC controller because of its known advantage with respect to the PID controller [26], and a VRFT controller due to its feasibility to be implemented since it does not use the system model in its synthesis procedure and it has shown good results in other industrial applications [8,33]. An important aspect to highlight in this study is that the controllers have been designed from the thermodynamic model used for product design, i.e., the model combines process measurements and empirical data considered for designing purposes. From the industrial point of view, the resulting validation of these advanced control strategies in an early design stage offers important technical information for improving the concurrent prototyping of an industrial box furnace.
3 Box Furnace System

The industrial box furnace considered in this study is made of ceramic fiber to keep good thermodynamic insulation; it has 5.8064 m² of area in the floor as well as in ceiling, and 15.9979 m² of total area among the four walls. The ceiling and walls thickness is 0.3048 m, whereas the floor thickness is 0.4572 m. Figure 1 shows a picture of the considered industrial box furnace. This heavy-duty box furnace is ideal for heat treatment processes (austenitizing, tempering, normalizing, annealing, and others), for steel forgings and castings; its design and dimensions reach temperatures up to 1588.7 K (1315.5 °C).

The furnace has six burners fitted with high-temperature slotted tiles. The burners project a jet of hot gases into the firing lanes of the kiln, tangentially along the long walls of the kiln at two elevations. These combustion gases entrain the air within the furnace to make a blend of the hot air which circulates at high velocity around and through the load as they move toward the flue opening in the furnace center.

To improve temperature uniformity inside the furnace, the burners are grouped into separate control zones. By separating the burners into multiple control zones the temperature differential within the kiln is minimized by adapting to load variations. Each burner (control zone) is provided with a modulating motor-controlled valve to maintain a uniform profile temperature. The variable excess air system allows high percentages of excess air to be introduced into the burner jet stream. This excess air provides the conditions of tempering heat outputs of the burners and thus maintains controlled temperatures with a high velocity volume for excellent mixing and temperature uniformity. Plus the excess air is the source for a high oxidizing atmosphere for binder burnout. Additionally, the excess air system and the burner turn-down actuation permit high rates of heat transfer without overheating the outside of the load.

Each burner is equipped with an individual fuel/air ratio regulator that varies the fuel in proportion to the combustion airflow. Also, each burner has a combustion air balancing valve, fuel shutoff solenoid valve, limiting orifice fuel valve, and gas and air metering orifices for individual burner adjustment. To assist in making and maintaining these adjustments, each burner is provided with valve pressure taps in the air and gas lines to be used with a manometer.

3.1 Industrial Box Furnace Instrumentation. For automatic control purposes (design and implementation), mainly those based on a model, the industrial process must be instrumented as much as possible to capture efficiently its behavior, usually by using analog and digital inputs (sensor signals) and outputs (actuator signals). In this study, the considered industrial furnace as a test-bed only explores the use of analog inputs/outputs.

For each zone, there is a motor actuator as well as a thermo-couple, such that each zone can be controlled separately. The motor actuator that controls the burner is an analog input, while the combustion air and gas volume flowrate variables analog outputs. Also, some other analog inputs/outputs will remain constant for this specimen. The set of digital inputs/outputs are given in a general manner as two arrows (one for inputs and the other for outputs) since they are not in the scope of this work, Fig. 2.

As previously mentioned, the furnace is heated by six natural gas burners to keep temperature uniformity with a total fuel input usually up to $1.5 \times 10^6$ W, equally distributed to the burners by the main pipe controlled using a specific digital control. The control unit of the furnace must provide a constant fuel to air ratio determining the desired oxygen concentration per volume in the flue gas (wet). To achieve a better temperature distribution, the burners are equipped with mass flow equipment, which provides good circulation of the hot flue gas. The isolation wall is assumed to be a homogeneous material (ceramic fiber) to have small heat losses through them. For the testing stage, the test-bed was fixed in a frame, which was sealed against the environment to prevent air leakage. With this basis, the set of the six operating zones are defined according to Fig. 3.

3.2 Typical Thermodynamic Behavior. A zero-dimensional thermodynamic model has been used in MATLAB/SIMULINK to represent the conservation equations of energy in the furnace operation at each sampling time, specifically in terms of the following Single Input–Single Output (SISO) relationship: fuel to burn–furnace temperature. However, the solved energy balance depends directly on the furnace design parameters such as the physical furnace dimensions, composition material in the furnace insulation, thermal load properties, oxygen-enriched conditions, etc., such that this model can be considered as a tool for an early furnace design [34]. The use of this model simplifies the control design and prototyping phase instead of using complex 2D models or computational fluid dynamics (CFD) simulations whose processing time is usually too much or the experimental platform that normally is only for validation purposes.

The thermodynamic analysis can be carried out in general for the complete furnace or divided by operating zones by applying the zone modeling method [35]. In the zone modeling method, usually all zones have the same temperature profile as reference (to keep uniformly the temperature in the thermal load), and depending on the load distribution and heat flux lost by the contiguous walls will be the fuel to supply in the corresponding burner.

To analyze the thermodynamic behavior of the mathematical furnace model, four operating configurations of the industrial box furnace were used. Table 1 summarizes the main parameters of the model in these setups to use them in the energy balance solver. For simplicity, in all operating cases, it is assumed that the heat due to radiation is zero and the heat losses through the walls keep constant at each sampling time, assuming that the temperature differential between the wall and environment does not have too much variation due to uniform insulation; the above assumption allows simplification of the thermodynamic analysis during the design process avoiding the use of temperature measurements of the wall or the use of complex CFD simulations. In this way, the heat flux losses through the walls are 10,780 W for all setup cases, and it corresponds to the heat flux lost due to the physical dimensions of the studied box furnace in this paper. Figure 4 illustrates the SISO behavior of the box furnace by using the zero-dimensional thermodynamic model for all setup cases.

Simulation data of a complex 2D model based on finite difference methods were used in the validation procedure of the zero-dimensional thermodynamic model as well as experimental data from an industrial box furnace. These results can be reviewed in
detail in Ref. [34], where the simple mathematical zero-order model approach follows the experimental furnace behavior and much more the 2D simulator dynamics.

3.3 Control Oriented Model. Model-based control strategies require a process model with a typical mathematical structure to be included in the synthesis of a controller. Indeed, MPC needs a state-space model representation, whose matrices must characterize the thermodynamic phenomena explained by the conservation equations of energy. In this sense, the MPC design phase first requires a state-space model capable to fit the SISO behavior of the box furnace for the four setup cases, i.e., only one process mathematical model independently of its operating conditions that represents the furnace thermodynamics using as input the fuel energy power and as output the furnace temperature.

Least squares method was used in the model identification procedure of the four furnace setup cases. As the first step, each data set
was used to model independently each furnace setup; thus, four state-space models were available for the same industrial furnace. The second step was to make cross-validation among the models and data sets such that the best model capable to represent all operating conditions will be the model for controller design purposes. Note in Fig. 5(c) that the state-space representation of the model fits also very well to the data provided by the complex 2D simulator.

Figure 5 illustrates the modeling results in the cross validation phase, the best model was obtained with the data of the setup case 3 achieving a fit representation upper than 91.45%.

Table 1  Model parameters for different thermodynamic operating conditions in the box furnace

| Model parameter | Setup case 1 | Setup case 2 | Setup case 3 | Setup case 4 |
|-----------------|-------------|-------------|-------------|-------------|
| \( m \) (kg)    | 1           | 5,000       | 4,000       | 6,000       |
| \( C_p \) (J/(kg K)) | 500       | 385         | 530         | 530         |
| \( T_{\text{initial}} \) (K) | 303.15     | 297.15      | 303.15      | 303.15      |
| \( H_G \) (MJ/m³) | 37.258     | 37.258      | 37.258      | 37.258      |
| \( X_{\text{air}} \) Variable [0 – 1] | 0.20       | 0.20        | 0.20        | 0.10        |
| \( V_{\text{VA}} \) (Sm³/s) | 0         | 0           | 0           | 8.33 × 10⁻³ |
| \( \dot{Q}_{\text{rad}} \) (W) | 0         | 0           | 0           | 0           |
| \( S_f \) | 1.2         | 1.2         | 1.2         | 1.2         |
| \( \dot{Q}_{\text{walls}} \) (W) | 10,780     | 10,780      | 10,780      | 10,780      |
| \( T_{\text{air}} \) (K) | 298.15     | 298.15      | 298.15      | 298.15      |
considering the setup case 3. In the Appendix, the numerical state-
space matrices obtained by the model identification procedure that
best represent the furnace thermodynamics in the considered four
operating conditions are detailed.

4 Controllers

The required system behavior, independently from its nature
dynamics, defines the control strategy and its actuation velocity.
In this case, special care must be taken that fired-gas flow variations
do not lead to combustion instabilities. Industrial furnaces have
low-frequency oscillations in the temperature signals so that a
slower control response is permissible.

As aforementioned was established, three controllers have been
chosen for this study: by simplicity and typical industrial use, the
PID controller; due to the recently reported advantages in similar
industrial furnaces, the MPC controller; and by its feasibility of
implementation, the VRFT controller. Following are summarized
the main features of these control approaches.

4.1 PID Control. Proportional-integral-derivative control
manipulates the system using the error dynamics between the set-
point and the process measured variable. PID control consists of
the sum of three control functions: (1) proportional band, (2) reset
action (integral component), and (3) rate action (derivative component).

A proportional band is defined as the amount of change in the
controlled variable required to drive the loop output from 0 to
100%. In a heating situation, if the process variable (temperature)
is below the proportional band, burners are continuously
fired by the controller. If the process value is above the proportional band,
the burners are shut off. In this way, as the process temperature
increases and tracks the set-point, the amount of heat must decrease
proportionally (Fig. 6). To determine the proper proportional band
setting, the time required to approach set-point must be balanced
with the process variable to withstand overshoot. A narrow propor-
tional band (means heat is on longer time) will approach set-point
quicker with the possibility of overshoot than a wide proportional
band. On the other hand, a wide proportional band begins cutting
back the heat input more opportunely.

Reset action (integral component) shifts the proportional band in
relation to the desired set-point, i.e., its main objective is to elimi-
nate the existing offset or droop between the output and set-point.
Rate action (derivative component) is used to mitigate sudden oscil-
lations in the process variable caused by the integral component.
The typical temperature control method in industrial furnaces is
the PID controller. When the measured temperature is different
from the set-point temperature, the heating system is controlled to
minimize the error. Generally, the PID method uses the following
equation to control the loop:

\[ u(t) = P (y_{sp}(t) - y(t)) + D \frac{d}{dt} (y_{sp}(t) - y(t)) + I \int (y_{sp}(t) - y(t)) dt \]  

(1)

where \( u(t) \) is the controller output, \( y_{sp}(t) \) in this case is the set-
point temperature, and \( y(t) \) is the furnace temperature (process
variable), such that the error value is \( e(t) = (y_{sp}(t) - y(t)) \); \( P \), \( I \),
and \( D \) are known as proportional, integral, and derivative gain,
respectively. In a PID control process, one of the most important
things is to set the \( P \), \( I \), and \( D \) gains. The objective is tuning these
constants so that the weighted sum of the proportional, integral, and derivative terms produces a controller output that steadily drives the process variable in the direction required to eliminate the error. Several methods can be used to determine the $P$, $I$, and $D$ gain values. One of them is Ziegler and Nichols’s approach, see Eq. (2), which is a practical method for experimentally estimating the PID parameters in linear SISO processes capable to be represented by a first-order transfer function, using the transient step-response analysis. Where $K$ is the process gain used to represent the magnitude of the effect of the control input on the process variable, $\tau$ is the process time constant used to represent the severity of the process lag, and $\theta$ is the deadtime used to represent the process delay once the control input has changed. In general, the aforementioned derivation of the first-order transfer function can be obtained analytically or graphically by a corresponding identification process.

\[
P = \frac{1.2\tau}{K}\theta I = \frac{2\theta}{K} D = \frac{0.5\theta}{K}
\]  

(2)

Sometimes, when the sensor measuring the furnace temperature is susceptible to other electrical interference, derivative action can cause the heater power to fluctuate wildly. In this case, $D = 0$ and a PI controller is often used instead of PID controller. The typical application of PD control in a furnace is to control hot/cold gases input when additional temperature control actions are required.

### 4.2 Model Predictive Control

Model predictive control (MPC) offers several important advantages in contrast with PID controllers [36]: (1) use the dynamic and static interactions between input-output in the controller design captured by the process model, (2) constraints on inputs and outputs are considered in a systematic manner, (3) the controller design is based on an optimization problem, and (4) accurate model predictions can provide early warnings of potential problems. Clearly, as with any other model-based control approach, the success of MPC depends on the accuracy of the process model.

The MPC calculations are based on the current measurements and predictions of the future values of the outputs. The main idea is to determine a sequence of control moves so that the predicted response (that depends on the process model) optimally moves to the set-point. The actual output of the process variable y, its predicted output $\hat{y}$ and the control input $u$ for a SISO process control are shown in Fig. 7. Note that at the current sampling time $k$, the MPC strategy computes a set of $M$ values of the input $\{u(k+i-1), i = 1, 2, \ldots, M\}$ so that a set of $P$ predicted outputs $\{\hat{y}(k+i), i = 1, 2, \ldots, P\}$ reaches the set-point in an optimal way. In this sense, $P$ is the prediction horizon while the control horizon $M$ corresponds to the control horizon. An interesting feature of the MPC is its receding horizon, of the total sequence of $M$ control signals, only the first one is applied to the controlled system at time $k$ and the rest is discarded. This procedure is repeated for each sampling time and achieves a feedback control as the optimization problem is performed when new measurements are made available. If the whole sequence would be applied it would be open-loop control.

For MPC based on linear process models, both linear and quadratic objective functions can be used in the control calculations. For an MPC with inequality constraints of saturation in the control input and predicted output, it can be considered the following quadratic objective function $J$ given by [36]

\[
\text{min } J = \hat{E}(k+1)^T Q \hat{E}(k+1) + \Delta U(k)^T R \Delta U(k) + S^T T S
\]

(3)

subject to

\[
\Delta U(k)_{\text{min}} \leq \Delta U(k)_{\text{max}} \leq \Delta U(k)_{\text{max}} 
\]

\[
\hat{Y}(k+1)_{\text{min}} \leq \hat{Y}(k+1)_{\text{max}} \leq \hat{Y}(k+1)_{\text{max}}
\]

such that the deviation error $\hat{E}(k+1)$ in the prediction horizon $P$ and the deviation error between the next $M$ control moves $\Delta U(k)$ are minimized. The predicted error vector, $\hat{E}(k+1)$, is defined as

\[
\hat{E}(k+1) = Y_{\text{sp}}(k+1) - \hat{Y}(k+1)
\]

(4)

where $\hat{Y}(k+1)$ is the predicted output vector over the prediction horizon $P$ and $Y_{\text{sp}}(k+1)$ is the corresponding set-point. In this case $\hat{Y}(k+1)$ corresponds to the furnace temperature dynamics, such that

\[
\hat{Y}(k+1) \triangleq [\hat{y}(k+1), \hat{y}(k+2), \ldots, \hat{y}(k+j), \ldots, \hat{y}(k+P)]^T
\]

(5)

where

\[
\hat{y}(k+1) = G_1 \Delta u(k) + \sum_{i=2}^{N-1} G_i \Delta u(k-i+1) + G_N u(k-N+1)
\]

(Effect of current control action) (Effect of past control actions)

\[
\hat{y}(k+2) = G_1 \Delta u(k+1) + G_2 \Delta u(k) + \sum_{i=3}^{N-1} G_i \Delta u(k-i+2) + G_N u(k-N+2)
\]

(Effect of future control action) (Effect of current control action) (Effect of past control actions)

\[
\hat{y}(k+j) = \sum_{i=1}^{j} G_i \Delta u(k+j-i) + \sum_{i=j+1}^{N-1} G_i \Delta u(k+j-i) + G_N u(k+j-N)
\]

(Effect of current and future control actions) (Effect of past control actions)

---

**Fig. 7** Typical representation for an MPC actuation
where $G$, for $i = 1, 2, \ldots, N$ is the transient coefficients in the step response of the state-space model of the furnace, obtained in the above section; $N$ is the number of the step-response coefficients such that the settling time is guaranteed [36], i.e., $N \times T_s > 5\tau + \theta$, where $T_s$ is the sampling period.

$Q$ is a positive-definite matrix to weight the predicted error in the minimization of $J$ and $R$ is a positive semi-definite matrix to weight the control effort also in the minimization of $J$, i.e., these matrices are used to weight the most important elements of $\hat{E}(k+1)$ and $\Delta U(k)$ in the prediction and control horizons, respectively. Both are usually diagonal matrices with positive diagonal elements.

The constraints on the control input differential and predicted output in Eq. (3), are usually hard and cannot be broken since they commonly represent a physical limitation, e.g., on the actuator. Therefore, these constraints usually are relaxed, especially those related to the predicted output. Constraints are relaxed by introducing new variables which are non-zero when the constraints are violated. These constraints usually are relaxed, especially those related to the predicted output. Constraints are relaxed by introducing new variables which are non-zero when the constraints are violated, these variables are called slack variables $\Delta$. To avoid violation of constraints when unnecessary, a penalty term is added to the objective in order to try to obtain a zero slack. In Eq. (3), matrix $T$ is the weighting matrix for the slack variables.

Vector $\Delta U(k)$ represents the MPC controller output and is calculated so that the objective function $J$ is minimized, such that

$$\Delta U(k) = K_c \hat{E}(k+1)$$

(6)

where $\hat{E}(k+1) = Y_0(k+1) - \hat{Y}_0(k+1)$ is the predicted unforced error vector, i.e., it is defined similarly to Eq. (4). In this case the predicted response $\hat{Y}_0(k+1)$ does not depend on current or future control actions. The controller gain matrix $K_c$ is defined to be

$$K_c = (G^T Q G + R)^{-1} G^T Q$$

(7)

where $G$ is referred to the dynamic matrix that can be obtained by the step-response of the state-space model representation of the industrial furnace, by considering the constraints in the control input, such that

$$G_{PwM} \Delta = \begin{bmatrix}
G_1 & 0 & 0 & \ldots & 0 \\
G_2 & G_0 & 0 & \ldots & 0 \\
G_3 & G_2 & G_1 & \ldots & \vdots \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
G_M & G_{M-1} & G_{M-2} & \ldots & G_1 \\
G_{M+1} & G_M & G_{M-1} & \ldots & G_2 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
G_P & G_{P-1} & G_{P-2} & \ldots & G_{P-M+1}
\end{bmatrix}$$

(8)

In this way, different design parameters must be specified to design an MPC. Here, are some typical recommendations [36]:

- The sampling period $T_s$ and model horizon $N$ must be chosen so that $N \times T_s$ is the settling time for the open-loop response.
- The control horizon $M$ usually is based on the following rules $5 \leq M \leq 2N$ and $N/3 \leq M \leq N/2$. As $M$ increases, the required computational effort increases.
- The prediction horizon $P$ is often selected to be $P = N + M$ so that the full effect of the last control inputs is taken into account. Less $P$ tends to make the controller more aggressive.
- $Q$ and $R$ are parameters of design to weight in the MPC the capability to minimize the tracking error as well as the conservative controller actuation.

### 4.3 Virtual Reference Feedback Tuning Control

Virtual reference feedback tuning (VRFT) is a general methodology for designing feedback controllers when the plant is unknown. The main features of the VRFT technique are as follows: (1) it is a direct method (no model identification of the plant is needed) and (2) it can be applied using a single set of data collected from the plant with no need for specific experiments nor iterations. VRFT was originally introduced for one degree-of-freedom (1-DoF) controllers and subsequently extended to two DoF controllers [37]. The 1-DoF control scheme shapes the reference-to-output transfer function as in Fig. 8.

![Fig. 8 Typical control system structure: 1-DOF control scheme](image)

Given a reference closed-loop model $M_c(z)$ that describes the desired transfer function from $r(k)$ to $y(k)$ and a family of parameterized controllers $\{C(z, \theta)\}$, the control objective is the minimization of the following two-norm model-reference criterion:

$$J(\theta) = \left[ \frac{P(z)C(z, \theta)}{1 + P(z)C(z, \theta)} - M_c(z) \right] W(z)^2$$

(9)

where $W(z)$ is a user-chosen weighting function to minimize the error between the model and the closed-loop response for a particular range of frequencies. VRFT returns the global optimum of $J$ when perfect matching between the reference-to-output transfer function and the reference model is possible, and it returns a good approximation of the best restricted complexity controller when the matching can only be approximately achieved. The inputs of the algorithm are as follows:

1. A set of measured I/O data $\{u(k), y(k), k = 1, \ldots, N\}$ collected during an open-loop or a closed-loop experiment on the plant.
2. When the plant output $y(k)$ is affected by noise, such noise generates a bias in the controller parameters. To counteract this biasing effect, an instrumental variable method can be used. There are two different choices for defining the instrumental variable [37]: (1) repeated experiment consists of performing a second experiment on the plant using the same input $u(k)$ as in the first experiment and collect the corresponding output $y(k)$; then, construct the instrumental variable as $\xi(k) = C(z, \theta) L(z)(M_c(z)^{-1} - 1)y(k)$, (2) identification of the plant consists of the identification of a model $P(z)$ of the plant from data and generate the simulated output $\hat{y}(k) = \hat{P}(z)u(k)$; then, construct the instrumental variable as $\tilde{\xi}(k) = C(z, \theta) L(z)(M_c(z)^{-1} - 1)y(k)$. $L(z)$ is a suitable filter to adjust the “ideal controller” to a given controller class (more practical) [33].
3. A reference model $M_c(z)$ that describes the desired transfer function from $r(k)$ to $y(k)$.
4. A user-chosen weighting function $W(z)$ that emphasizes the importance of matching the reference-to-output transfer function with $M_c(z)$ at different frequencies.

The output of the algorithm is a family of linearly parameterized controllers:

$$C(z, \theta) = \theta_1 C_1(z) + \theta_2 C_2(z) + \ldots + \theta_k C_k(z)$$

(10)

where $\{C_1(z), C_2(z), \ldots, C_k(z)\}$ are transfer functions that represent the basis of the controller and $\theta \in \mathbb{R}^k$ the corresponding gains that minimize the model-reference criterion in Eq. (9). In general, the idea behind the VRFT method can be summarized in four steps:

1. Generate a set of I/O data $\{u(k), y(k), k = 1, \ldots, N\}$, by a single experiment on the plant.
2. Given the measured $y(k)$, generate in your computer a reference signal $r(k)$ such that $M_c(z)\hat{r}(k) = y(k)$, where $M_c(z)$ is the desired reference model. $r(k)$ is called virtual reference because it was not used to generate $y(k)$ and it only exists as a computer file. Notice that $y(k)$ is by the construction of $r(k)$
the desired output of the closed-loop system when the reference signal is $r^*(k)$, Fig. 9.

3) Generate the corresponding tracking error $e^*(t) = r^*(t) - y(t)$.

4) Even though plant $P(z)$ is not known, we know that when $P(z)$ is fed by $u(k)$ (the currently measured input signal), it generates $y(k)$ as an output. Therefore, a good controller is one that generates $u(k)$ when fed by $e^*(k)$. The idea is then to search for such a controller. Since both signals $u(k)$ and $e^*(k)$ are known, this task boils down to the problem of identifying the dynamical relationship between $e^*(k)$ and $u(k)$.

5 Simulation Results and Discussion

In this section, the simulation results of the three considered controllers as well as a comparative analysis among them by using the same metrics and performance evaluation are presented. In the end, some recommendations are given.

5.1 Design of Controllers for the Industrial Box Furnace. For the PID controller design, from the state-space model obtained with the four setup cases it was obtained a first-order transfer function with a time delay between the fuel energy power ($u(t)$) and the furnace temperature ($y(t)$). Transient step response of this system was used to identify the model parameters $K = 0.015 \, \text{K/\%}$, $\tau = 7.3 \, \text{min}$, and $\theta = 5 \, \text{s}$ which then were used to estimate the PID parameters according to Eq. (2).

On the other hand, Fig. 10 shows the block diagram of a control system with an MPC approach applied for an industrial box furnace. Note that yellow blocks represent the three most important features to consider for designing and implementing an MPC. In this case, the state-space model must represent the most typical operating conditions of the industrial furnace with high accuracy. In this case, as previously it was shown the state-space representation has a modeling fit upper than 91.45%. According to the basic rules of design [36], the control horizon was $M = 20$, the prediction horizon was $P = 75$ with a sampling time $T_s$ (which is sufficiently small for capturing the thermodynamic phenomena in the furnace operation).

The design of the controller based on the VRFT algorithm was based on a PID-based feedback control structure. The PID controller structure was selected because of its easy-to-implement characteristic in commercial systems. The reference model $M_r(z)$ was selected similar to the open-loop transfer function dynamics with unitary gain. The set of I/O data $\{u(k), y(k), k = 1, \ldots, 263\}$ was generated using the case one with a sampling period of 40 s; the setup case 1 of the furnace was also used to define $M_r(z)$. The algorithm VRFT identifies the dynamical relationship between $e^*(k)$ and $u(k)$.
u(k) using the transfer function of the PID controller. The resulting controller transfer function $C(z)$ was

$$C(z) = \frac{130z + 124.9}{z - 0.8958} \quad (11)$$

5.2 Performance Evaluation. The performance evaluation consists of the simulation of a closed-loop control system; the considered model represents the furnace operation in the setup case 3 that has modeling fit upper than 91.45% using cross-validation with the other setup cases. The controller is one of the above mentioned (PID, MPC, or VRFT), and the temperature reference can be one of the two simulated experiments (step test or temperature profile test) with transient response plots, a periodogram, and quantitative indexes, Fig. 11.

In order to validate the performance of each controller for several system configurations, three cases of box furnace specifications described in Table 1 were used as models; the setup case 3 was not used in this validation task because this model was the basis for the controllers’ design. The output of the controller will be

![Fig. 12 Simulation results of the control system considering the step test (left plots: (a) closed-loop control performance, (c) energy expenses, (e) tracking error to the set-point and (D) power spectral density of the fuel consumption) and the temperature profile test (right plots: (b) closed-loop control performance, (d) energy expenses, (f) tracking error to the set-point, and (h) power spectral density of the fuel consumption) for the box-furnace using the setup case 1. Qualitative assessment for the PID, MPC, and VRFT controllers’ performance.](image-url)
The simulation tests consist of (1) a step-response in the set-point of 2500°F and (2) the temperature profiles for each setup case of interest.

5.2.1 Qualitative Proofs. The qualitative performance consists of three transient response plots and the power spectral density of the controller output, Fig. 11. The transient response plots are as follows: (1) time versus controlled temperature and temperature reference, (2) time versus control system tracking error, and (3) time versus controller output. The power spectral density of the controller output will allow analyzing the feasibility of actuation in realistic application with regard to the actuator’s bandwidth.

5.2.2 Quantitative Index. Two quantitative indexes will be used for the validation of each controller performance; the normalized root-mean-square deviation (NRMSD), and the system manipulation power $P_{man}$. The NRMSD facilitates the comparison between cases that have set-points with different scales. The normalization measure is the range (defined as the maximum value minus the minimum value) of the measured data:

$$NRMSD = \frac{RMSD}{Y_{\text{max}} - Y_{\text{min}}}$$

where $RMSD = \sqrt{\frac{\sum_{t=1}^{N} (r(t) - y(t))^2}{N}}$

Fig. 13 Simulation results of the control system considering the step test (left plots: (a) closed-loop control performance, (c) energy expenses, (e) tracking error to the set-point, and (g) power spectral density of the fuel consumption) and the temperature profile test (right plots: (b) closed-loop control performance, (d) energy expenses, (f) tracking error to the set-point, and (h) power spectral density of the fuel consumption) for the box-furnace using the set-up case 4. Qualitative assessment for the PID, MPC and VRFT controllers’ performance.
The system manipulation power $P_{\infty}$ will indicate the power of the manipulation signal in order to validate the expended energy by the controller:

$$P_{\infty} = \frac{1}{2N+1} \sum_{i=1}^{N} E_{\infty}$$

(13)

where $E_{\infty} = \sum_{i=1}^{N} |u(i)|^2$.

5.3 Simulation Results. Figure 12 illustrates the simulation results when the box furnace has the setup case 1. In this case, when the temperature reference is a step, the PID control response tracks faster and better the set-point than others controllers, Fig. 12(a), but its actuation is more aggressive with higher bandwidth of actuation, indeed Fig. 12(g) shows that the PID has the greater expended energy on the burners. On the other hand, the MPC has less tracking error than the VRFT controller but slightly greater than the PID; however, the MPC has much softer actuation than the PID and in consequence lower expended energy by the controller.

The difference among the controllers’ performances is more notable in the simulated temperature profile test. Figure 12(b) shows that the MPC and PID controllers track well the target and the VRFT control has an offset; indeed, in Fig. 12(f) this issue of the VRFT can be clearly confirmed. In this test, the hard and highly switching actuation of the PID is notorious in contrast to the VRFT and MPC actuation signals, Fig. 12(d), this issue of course generates more expended energy on the burners and all components of the actuation system.

When the box furnace model has the setup case 4 in the controlled system simulation, the results are qualitatively similar to the previously discussed, Fig. 13. In both step and temperature profile tests, the VRFT presents an offset in its controlled output, while the best one to follow both targets is the MPC controlled output, Figs. 13(a) and 13(b); on the other hand, the PID control generates too much overshoot in the controlled output during the step test. In this furnace set-up case, also the PID demands highly switching actuation on the burners in comparison to the MPC and VRFT controllers, Figs. 13(c) and 13(d), and by consequence higher expended energy in all control and actuation components.

The aforementioned qualitative results can be confirmed by the following quantitative performance indexes. Table 2 presents the expended energy power by the control approaches as well as the NRMSD tracking error-index, considering the step test as temperature target in all furnace set-up cases except case 3 because this model was the basis for the controllers’ design. In all cases, the PID control has the lowest tracking error index but the highest expended energy power on the burners. The MPC maintains an equilibrium between actuation and performances such as its design defines, the MPC has 62.4% lowest error in case 1 with respect to the VRFT control, 66.9% in case 2, and 61.3 % in case 4.

For the temperature profile test, Table 3 reports the quantitative results obtained by the three controllers, using all furnace setup cases except case 3. In this test, the MPC approach also has a good balance between performance and actuation, it has a similar tracking error than the PID control but with considerably lower energy power consumption by the controller. The VRFT in this test shows an important offset with respect to the target, a reason that causes too much tracking error. MPC improves the temperature tracking performance up to 82.4% in case 1, 86.3% in case 2, and 87.2% in case 4 with respect to the VRFT controller.

6 Conclusion

In industrial practice, the automatic control systems usually are tuned by a heuristic process dependent on the control engineer’s expertise and trial and error iterations. In the end, the industrial process such as a furnace has acceptable performance but not optimal. In this sense, the main objective of this paper is the design and validation of an advanced control strategy in the early design stage of the furnace achieving three goals: (1) to decrease the controller tuning time during the furnace commissioning process, (2) to improve the furnace performance with respect to classical industrial controllers, and (3) to decrease the system energy expenses.

For the above purpose, different control approaches have been compared in a simulation environment whose model comes from an industrial box furnace during its early design stage. The three controllers chosen for this study are: the PID controller by its simplicity and typical industrial use, due to the recently reported advantages in similar industrial processes the MPC and by its feasibility of implementation the VRFT controller.

For modeling the industrial furnace, a physical-design-based thermodynamic model was used in four different operation setups. The solved energy balance depends directly on the furnace designing parameters such as the physical furnace dimensions, composition material in the furnace insulation, thermal load properties, oxygen-enriched conditions, etc., such that this model can be considered as a tool for an early furnace design. The use
of this model for temperature control design will reduce the controller tuning time during the furnace commissioning process. Two-dimensional complex model simulations based on finite difference methods were used to validate the model used in the controllers' design.

By considering two simulation tests, step response and temperature profile, the MPC approach shows the best balance between performance and actuation, it has a similar tracking error than the PID control but with considerably lower energy power consumption by the controller. The hard and highly switching actuation of the PID in both tests is notorious in contrast to the VRFT and MPC actuation signals; thus, the PID generates more expended energy on the burners and all components of the actuation system. For being a controller whose design is process model-free, the VRFT is an interesting controller but the data-set used in its tuning must characterize all process dynamics to avoid bad tracking. In this case, the use of a data set from only one furnace setup case generates considerable offset with respect to the target, a reason that causes too much tracking error in both tests. MPC improves the temperature tracking performance up to 66.9% in the step test and 87.2% in the temperature profile test with respect to the VRFT controller.

The MPC approach, or even the VRFT with better tuning, can be implemented through an embedded control system in an industrial furnace. In this situation, the control engineer will expend less time since the same basis model used for manufacturing the furnace will be used to design the control system, such that the time-to-market manufacturing can decrease.

Acknowledgment
Authors thank CONACyT for the partial financial support in the Project PEI number 250460.

Nomenclature

\[ m = \text{load mass (kg)} \]
\[ C_p = \text{specific heat capacity of the load (J/(kg K))} \]
\[ H_f = \text{fuel/gas heat content (J/m}^3\) \]
\[ Q_{fuel} = \text{heat flux of the fuel (W)} \]
\[ Q_{load} = \text{heat flux to the load (W)} \]
\[ Q_{walls} = \text{heat losses through the walls (W)} \]
\[ T_{air} = \text{ambient air temperature (K)} \]
\[ T_w = \text{wall temperature (K)} \]
\[ V_{CA} = \text{combustion air volume flowrate (Sm}^3\)/s\)
\[ V_{DA} = \text{diffusion air volume flowrate (Sm}^3\)/s\)
\[ V_G = \text{fuel/gas volume flowrate (Sm}^3\)/s\)
\[ X_{ex} = \text{excess air} \]
\[ sf = \text{security factor} \]

Appendix: Numerical State-Space Model of the Furnace

Continuous-time identified state-space model:

\[
\dot{x}(t) = Ax(t) + Bu(t)
\]
\[
y(t) = Cx(t) + Du(t)
\]

\[ A = \begin{bmatrix}
-7.507 & 0.8765 & -0.0030 & 0.0002 & -0.0004 & -0.0005 & 0.0002 & 0.0004 & -0.0001 & -0.0002 \\
-5.59 & -0.7401 & 0.0034 & 0.0001 & 0.0006 & -0.0004 & -0.0003 & -0.0004 & 0.0001 & 0.0001 \\
-2.374 & -0.7372 & -0.2141 & -0.0636 & -0.0442 & -0.0782 & 0.0346 & 0.0276 & 0.0107 & -0.0143 \\
1.203 & 0.3883 & 0.1917 & -0.0771 & -0.0102 & 0.0239 & -0.0182 & -0.0222 & 0.0187 & -0.0001 \\
0.0242 & -0.1714 & 0.3765 & 0.5777 & 0.3816 & 0.7191 & -0.2017 & -0.1964 & -0.2527 & 0.2074 \\
-0.191 & -4.218 & 0.6461 & 3.794 & -1.223 & -3.597 & 0.4378 & 1.608 & -0.608 & -1.681 \\
5.277 & 4.472 & -5.133 & -9.163 & -3.413 & 5.959 & -3.029 & -4.243 & 2.827 & 0.5647 \\
3.26 & 4.065 & -5.936 & -9.686 & -3.484 & 1.036 & -0.244 & -2.005 & 3.005 & 0.406 \\
-0.3932 & -0.3802 & 0.4937 & 0.7893 & 0.0286 & 0.2236 & -0.5882 & -0.0566 & -0.0826 & -0.412 \\
6.174 & 3.383 & -2.136 & -4.845 & -0.4856 & 2.182 & -3.482 & -1.559 & 2.557 & -1.756 \\
\end{bmatrix}
\]

\[ B = \begin{bmatrix}
-0.0382 & \vdots & -943.4 & \vdots \\
-0.0013 & \vdots & 2975 & \vdots \\
0.426 & \vdots & -6730 & \vdots \\
0.0759 & \vdots & -1.072e+04 & \vdots \\
-4.897 & \vdots & -1.003e+04 & \vdots \\
1.085 & \vdots & -719.6 & \vdots \\
10.93 & \vdots & 1176 & \vdots \\
32.2 & \vdots & -1871 & \vdots \\
-3.713 & \vdots & -1265 & \vdots \\
10.11 & \vdots & -197.6 & \vdots \\
\end{bmatrix}
\]

\[ C = \begin{bmatrix}
\vdots & \vdots \\
\end{bmatrix}
\]

\[ D = 0 \]

References

[1] Edwards, C., and Spurgeon, S., 1994. “Application of Sliding Modes to the Control of Industrial Furnaces,” 20th International Conference on Industrial Electronics, Control and Instrumentation, IECON’94, Bologna, Italy, Vol. 3, IEEE, pp. 1443–1448.
[2] Stojanowski, G., and Stankowski, M., 2013. “Comparison of Predictive Control Methods for High Consumption Industrial Furnace,” Sci. World J., 2013, p. 279642.
[3] Sobol, W., Korwin, M. J., Goraczko, M., and Balazinski, M., 1999. “Fuzzy Logic Control of Industrial Heat Treatment Furnaces,” 18th International Conference of the North American on Fuzzy Information Processing Society, NAFIPS, New York, IEEE, pp. 839–843.
[4] Hu, Y., Tan, C., Broughton, J., Roach, P. A., and Varga, L., 2018. “Nonlinear Dynamic Simulation and Control of Large-Scale Reheating Furnace Operations Using a Zone Method Based Model,” Appl. Therm. Eng., 135, pp. 41–53.
REFERENCES

[1] Qin, S. J., and Badgwell, T. A., 2003, “A Survey of Industrial Model Predictive Control Technology,” Control Eng. Pract., 11(7), pp. 733–764.

[2] Steinbock, A., Wild, D., and Kugi, A., 2013, “Energy-Efficient Control of Continuous Reheating Furnaces,” IFAC Proc. Vol., 46(16), pp. 359–364.

[3] Zuo, W.-H., Liu, B.-C., and Zhu, W.-J., 2015, “An Improvement of Decoupling Control Research of Gas Heating Furnace Temperature System,” 12th International Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), Chengdu, China, IEEE, pp. 102–106.

[4] Campi, M. C., Leechihi, A., and Savarese, S. M., 2002, “Virtual Reference Feedback Tuning: A Direct Method for The Design of Feedback Controllers,” Automatica, 38(8), pp. 1337–1346.

[5] Bekker, I., Craig, I., and Pistorius, P., 2000, “Model Predictive Control of An Electric Arc Furnace Off-Gas Process,” Control Eng. Pract., 8(4), pp. 445–455.

[6] Bauer, M., and Craig, I. K., 2008, “Economic Assessment of Advanced Process Control-a Survey and Framework,” J. Process. Control., 18(1), pp. 2–18.

[7] Wei, D., Craig, I. K., and Bauer, M., 2007, “Multivariate Economic Performance Assessment of An Mpc Controlled Electric Arc Furnace,” ISA Transactions, 46(3), pp. 429–436.

[8] Zhao, C., Zhao, Y., Su, H., and Huang, B., 2009, “Economic Performance Assessment of Advanced Process Control With LQG Benchmarking,” J. Process. Control., 19(4), pp. 557–569.

[9] Thwaites, P., 2007, “Process Control in Metallurgical Plants-From An Xstralal Perspective,” Ann. Rev. Control, 31(2), pp. 221–239.

[10] Lu, Z., XIAO, B., and Tiu, Y., 2012, “Improved Disturbance Observer (dob) Based Advanced Feedback Control for Optimal Operation of a Mineral Grinding Process,” Chin. J. Chem. Eng., 20(6), pp. 1206–1212.

[11] Precup, R.-E., and Hellendoom, H., 2011, “A Survey on Industrial Applications of Fuzzy Control,” Comput. Indus., 62(3), pp. 213–226.

[12] Feng, G., 2006, “A Survey on Analysis and Design of Model-Based Fuzzy Control Systems,” IEEE Trans. Fuzzy Syst., 14(5), pp. 676–697.

[13] Jin, X., Wang, S., Huang, B., and Forbes, F., 2012, “Multiple Model Based LPV Soft Sensor Development With Irregular/Missing Process Output Measurement,” Control Eng. Pract., 20(2), pp. 165–172.

[14] Xu, Z., Zhao, J., Qian, J., and Zhu, Y., 2009, “Nonlinear Mpc Using An Identified LPV Model,” Ind. Eng. Chem. Res., 48(6), pp. 3043–3051.

[15] Bars, R., Colaneri, P., De Souza, C. E., Dugard, L., and Scherter, C., 2006, “Theory, Algorithms and Technology in the Design of Control Systems,” Ann. Rev. Control, 30(1), pp. 19–30.

[16] Hangos, K. M., Bokor, J., and Szederkenyi, G., 2006, Analysis and Control of Nonlinear Process Systems, Springer Science & Business Media.

[17] Goodhart, S., Burnham, K., and James, D., 1991, “A Bilinear Self-Tuning Controller for Industrial Heating Plant,” International Conference on Control ‘91, Edinburgh, UK, IET, pp. 779–783.

[18] Deguan, S., Gui, G., Zhou, G., and Peng, X., 2012, “Application of Expert Fuzzy PID Method for Temperature Control of Heating Furnace,” Procedia Eng., 29, pp. 257–261.

[19] Wang, H., Xie, H., Shi, L., Ma, L., and Bai, Y., 2014, “Applications of Fuzzy-PID to the Firing Process Control System of High-Temperature Shuttle Kiln for Zirconia-Alumina Products,” 11th World Congress on Intelligent Control and Automation (WCICA), Shenyang, China, IEEE, pp. 4441–4446.

[20] Zhang, R., Xue, A., and Gao, F., 2014, “Temperature Control of Industrial Coke Furnace Using Novel State Space Model Predictive Control,” IEEE Trans. Indus. Inform., 10(4), pp. 2084–2092.

[21] Parshoosthahan, R., 2008, “Evaluation and Improvement of Heat Treat Furnace Model,” Ph.D. thesis, Worcester Polytechnic Institute.

[22] Carlberg, H., and Iredahl, H., 2016, “Modeling And Temperature Control of An Industrial Furnace,” Master’s thesis, Linkoping University.

[23] Rosas, J. D., Morilla, F., and Vilanova, R., 2012, “Multivariable PI Control for a Boiler Plant Benchmark Using The Virtual Reference Feedback Tuning,” IFAC Proc. Vol., 45(3), pp. 376–381.

[24] Roman, R.-C., Radac, M.-B., Precup, R.-E., and Petriu, E. M., 2016, “Data-Driven Model-Free Adaptive Control Tuned by Virtual Reference Feedback Tuning,” Acta Polytech. Hungarica, 13(1), pp. 83–96.

[25] Formentin, S., De Filippi, P., Corno, M., Tanelli, M., and Savarese, S. M., 2013, “Data-Driven Design of Braking Control Systems,” IEEE Trans. Control Syst. Technol., 21(1), pp. 186–193.

[26] Previdi, F., Fico, F., Savarese, S. M., Bellotti, D., and Pesenti, I., 2012, “Direct Design of A Velocity Controller and Load Disturbance Estimation For A Self-balancing Industrial Manipulator,” Mechatronics, 22(8), pp. 1177–1186.

[27] Campi, M. C., and Savarese, S. M., 2006, “Direct Nonlinear Control Design: The Virtual Reference Feedback Tuning (VRFT) Approach,” IEEE Trans. Automat. Contr., 51(1), pp. 14–27.

[28] Tudon-Martinez, J., Cantu-Perez, A., Cardenas-Romero, A., and Lozoya-Santos, J., 2019, “Mathematical Model-Based Design Of An Industrial Box Furnace,” Appl. Therm. Eng., 161, p. 114153.

[29] Tan, C., Jenkins, J., Ward, J., Broughton, J., and Heeley, A., 2013, “Zone Modelling of the Thermal Performances of a Large-Scale Bloom Reheating Furnace,” Appl. Therm. Eng., 50, pp. 1111–1118.

[30] Seborg, D., Mellichamp, D., Edgar, T., and Doyle, F., 2010, Process Dynamics and Control, John Wiley & Sons Inc., Hoboken, NJ.

[31] Carle, A., Torricelli, F., Campi, M., and Savarese, S., 2019, “A Toolbox for Virtual Reference Feedback Tuning (VRFT),” 18th European Control Conference (ECC), IEEE, pp. 4252–4257.