Model predictive control for temperature regulation of professional ovens

Juan Marcelo Castellino[1,2], Francesco Forte[2], Gianfranco Fenu[1] and Felice Andrea Pellegrino[1]

***Abstract*— We apply the model predictive control (MPC) strategy in an industrial setting, specifically for controlling the temperature of Combi Oven Professional Appliances. The proposed method takes into account input and output constraints, as well as the presence of multiple sources of disturbance. The workflow includes identifying and validating a model of the cell temperature and incorporating disturbance models. MPC is implemented using a state-space formulation. The proposed method shows significant energy saving and tracking error reduction with respect to the current oven control; its effectiveness has been demonstrated through several tests carried out on a professional oven.**

I. INTRODUCTION

The food processing industry, from small to highly technological business, is facing increasing impact from the expanding fast food market, heightened consumer awareness regarding food quality, the trend of ordering various cuisines online, and more stringent government regulations. The energy consumption is a critical factor that is taken into account when running a restaurant service and during the operation of a professional kitchen. Since the oven appliance is the prominent part of a kitchen, then as a result, the performance of the oven in regulating the temperature of the food is involved and plays a very crucial role in the professional kitchen.

In most cases, the temperature of industrial oven systems is regulated by proportional-integral-derivative (PID) algorithms [13] [14] because they are easy to implement. However, in some cases there are considerable time delays and unpredictable disturbances that affect the performance of these algorithms.

When these time delays are present, the effect of control actions and disturbances takes time to be seen on the controlled variables. In most cases this time is unknown beforehand. To solve these problems, various approaches have been used, based, e.g., on the Smith predictor (SP), fuzzy logic controller, neural networks (NN), and the combination of these. Among them, the fuzzy PID algorithm [15] shows an improvement in terms of robustness by setting the controller parameters online. However, it takes a long time to build fuzzy rules for all possible cases and the performance of the regulation depends to a large extent on user practical experience. The NN algorithms [16] [17] exhibit a strong adaptation to changing control objectives even though, in contrast, they have to deal with a computational burden execution online and neural training work. Therefore, they pose some challenges for onboard implementation.

The requirements we need in this field are to predict the behaviour of the professional appliance and to supply the optimal amount of energy, in order to have a smarter, better and sustainable solution for this kind of food service machine. And this means making sure that the cooking points of the professional equipment meet the economic objectives, taste and quality of food, along with the physical limitations of supplied energy when it is needed. A possible approach for the problem at hand is model predictive control (MPC). Since it is inherently multiple-input multiple-output (MIMO) and takes explicitly into account the input/output constraints, it has been successfully applied to thermal processes as well as to systems with large inertia and time-delay. Generally, MPC algorithms rely on methods such as Dynamic Matrix Control (DMC) method and Generalized Predictive Control (GPC) method, wherein they are based on linear input/output models, such as impulse or step response models and transfer functions [1], [2]. In the most current research literature, MPC is formulated almost always in the state space [5]. For all the aforementioned reasons, a Model Predictive Control technique based on state-space model is our research and development direction for industrial oven systems. In this work, we apply MPC to control the temperature of a professional oven, after identifying and validating a model, and taking into account input and output constraints, as well as various sources of disturbance.

The paper is organized as follows. Section II presents the considered plant and its principal functionalities. Section III gives some details about control requirements. Section IV describes our work flow from the prototyping, the modeling and the MPC formulation. Section V conducts the simulation, experiments and discusses the results on the Oven performance to further validate the effectiveness of the proposed method. Final conclusions are drawn in Section VI.

II. APPLIANCE DESCRIPTION

The research was carried out by using the Skyline Combi Oven as a test plant. This kind of oven cooks inside the cell with hot air by convection, steam or a combination of both. When the convection function is selected, dry heat is circulated around the oven by a fan. In the steam function, a boiler generates the steam which flows onto the cavity through the difference of pressure produced by the fan.

[1]Università di Trieste, Dipartimento di Ingegneria e Architettura, 34127 Trieste, Italy. Email: juanmarcelo.castellino@phd.units.it, {fapellegrino, fenu}@units.it

[2]Electrolux Professional Spa. 33170, Pordenone, Italy. Email: {juan-marcelo.castellino, francesco.forte}@electroluxprofessional.com

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III. TEMPERATURE CONTROL SPECIFICATIONS

According to the plant analysis, the following challenges were found:

- All oven control actuators are subject to power constraints, for example, the heating power control is one directional where only positive values can be provided.
- The continuous change of the working point that a cooking process achieves in order to execute a recipe.
- The temperature transition time should be as quick as possible. In daily use practices, the ideal temperature setpoint is only reached after a certain time but the safety requirement [3] must be achieved in a short time.
- A minimal temperature overshoot should be considered. The food degradation becomes an important issue when the temperature in the oven cell rises higher [4] than the required setpoint.
- The presence of multiple sources of disturbance that cause the temperature fluctuations. For example, some disturbances are: periodic changes in the direction of the fan rotation speed, the way the food molecules absorb energy, the steam generation resulting from cooking the food and the flow of steam produced by the boiler.

As a result, the average temperature deviates from the ideal temperature setpoint. The aforementioned reasons motivate us to introduce a disturbance rejection control to compensate for the disturbances when they are present.

IV. MPC DESIGN FLOW

Our implemented Model Predictive Control (MPC) design flow consists of the following path: first, it starts from the prototype building to reproduce the behaviour of the Combi Oven appliance and to monitor the control and measures in real time of the actual working conditions. Then from there, the identification experiment, without load inside the cell, is executed by applying a pseudorandom binary sequence at the power input and collecting the data. Subsequently, the Subspace Identification method is used to obtain a mathematical model of the plant. This procedure is completely off-line. Next, the MPC strategy is established with the performance index (cost function) and the constraints setup of the plant. After this, a custom quadratic program (QP) solver is implemented in order to be suitable for the computational capabilities of our electronic hardware. Finally, the tests are carried out and the results are validated.

A. Prototyping

The approach that was followed is the On-Target Rapid Prototyping. A prototype was built using pre-existing sensors, actuators and the actual mechanical structure. We substituted the electronic part with a programmable logic controller (PLC) and dedicated I/O modules as shown in Figures 1 and 2. This approach allowed us to explore and evaluate the MPC control algorithm by monitoring all variables during the operation.

Fig. 1: Front view of the prototype Skyline Combi Oven.

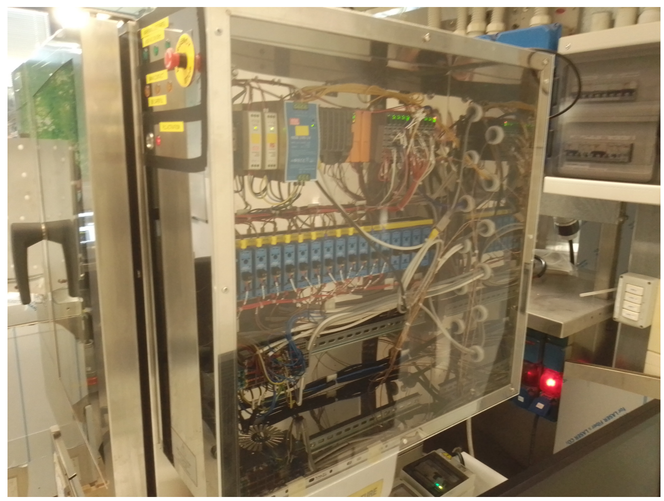

Fig. 2: Detail of PLC used for Rapid Control Prototyping.

B. Modeling

The goal was to build a "control-oriented" discrete-time model which is used to predict the free response of the plant. To obtain this type of model, it is necessary to evaluate the different construction possibilities. From the physical point of view, we need:

- the dynamic characterization of components whose development is expensive in terms of time and resources;
- the integration of these characterizations in a model, resulting in a non-linear model.

Therefore, these pose some difficulties for on-board implementation such as computational time and memory. To overcome these barriers, the subspace identification method [6] was implemented with our dataset to estimate a black-box linear model of the Combi Oven. Since this model is linear, it makes the calculation of the best input relatively straightforward. This model is formulated in state space and

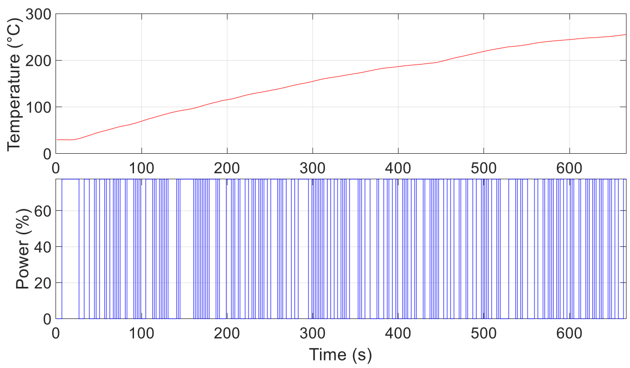

Fig. 3: The measured temperature (red) and the heating power percentage (blue) enforced as a PRBS for identification purposes.

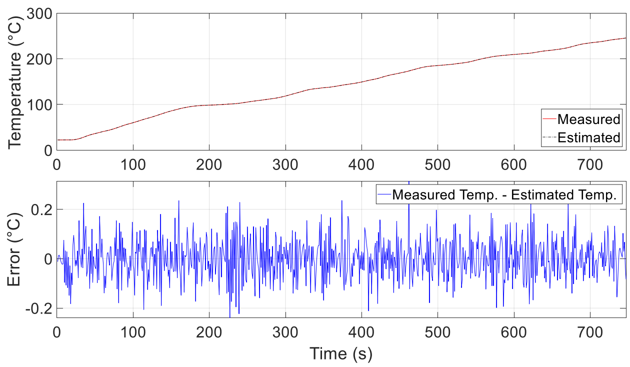

Fig. 4: The upper part shows the measured (red) and the estimated temperature (black); the lower part shows the error signal between them.

has the following form:

$$x(k+1) = Ax(k) + Bu(k) + w(k) \tag{1a}$$
$$y(k) = Cx(k) + Du(k) + v(k), \tag{1b}$$

where y, x, u, w and v are the system outputs, states, inputs, state noises, and output measurement noises, respectively. A, B, C and D are system matrices with appropriate dimensions. In our open-loop identification experiment, we used the concept of persistency of excitation [7], where the input signal used is a pseudo-random binary signal (PRBS) generated by using a shift register [8] of order 10. Its period is equal to $M = 2^{10} - 1$. Therefore, the duration of the experiment was chosen less than M, in order to obtain sufficient information from the system and to ensure that the correlation function of this pseudo-random signal resembles the correlation function of a white random noise. In addition, the identification experiment was carried out with the empty oven cell. The signals were sampled using a constant sampling interval. This implied that the power input and the temperature output data were recorded in discrete time as shown in Figure 3, where the clock period was equal to one second. Next, the identified 3$^{\text{rd}}$ order model was tried out on experimental data taken from a test without the load inside the cell and with a different feedback coefficient configuration of the shift register used for generating input power. This data was not used in the previous identification experiment. The test presented a good estimate with fewer residues than the measurement of the plant temperature as shown in Figure 4 . Furthermore, from Figure 5 , the conventional residual analysis can be observed in which R_e is the correlation among the residuals themselves [7] to exhibit the residuals that are uncorrelated. Wherein, R_{eu} is the covariance between residuals and past inputs [7] to reveal the independence between them. The R_e and R_{eu} are inside the confidence interval of 99%. Then, this identified linear discrete-time model is descriptive enough to capture the most significant dynamics of the plant when the oven is empty. It is also simple enough to solve the MPC optimization problem. The model (1) can be augmented with additional states [9] to represent the effect of the disturbances, previously mentioned III at the input and output of the system. Specifically, it was considered a ramp-shaped load disturbance entering the system whose model is given as:

$$x_r(k+1) = A_r x_r(k) \tag{2a}$$
$$d_r(k) = C_r x_r(k) \tag{2b}$$
$$A_r = \begin{bmatrix} 1 & 0 \\ h & 1 \end{bmatrix} \tag{2c}$$
$$C_r = \begin{bmatrix} 0 & 1 \end{bmatrix} \tag{2d}$$

where h is the sampling time. On the other hand, the disturbance that affects the temperature measurement behaves persistently and it is related to the frequency ω_1 of the fan rotation change. The amplitudes of the first three harmonics have a greater weight and vary according to the load distribution in the cell. Thus, we used the following model:

$$x_{si}(k+1) = A_{si} x_{si}(k) \tag{3a}$$
$$d_{si}(k) = C_{si} x_{si}(k) \tag{3b}$$
$$A_{si} = \begin{bmatrix} \cos(\omega_i h) & -\sin(\omega_i h) \\ \sin(\omega_i h) & \cos(\omega_i h) \end{bmatrix} \tag{3c}$$
$$C_{si} = \begin{bmatrix} 1 & 0 \end{bmatrix} \tag{3d}$$
$$\text{with} \quad i = 1, 2, 3$$

To guarantee zero steady state errors, the MPC controller is designed to contain an integral action. To achieve the integral action we use a disturbance observer with the extended

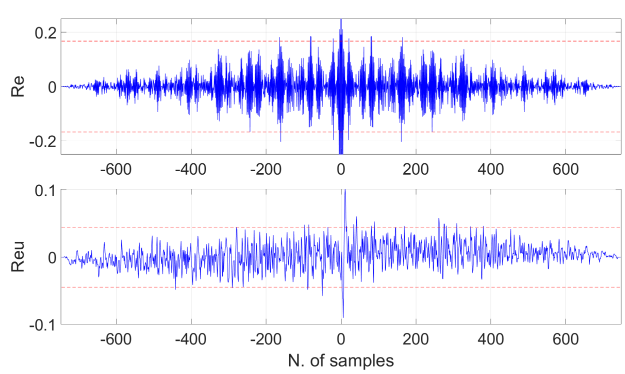

Fig. 5: Correlation among the residuals (upper part) and covariance between the residuals and past inputs (lower part). The red dashed lines represent the lower and the upper limits of the 99% confidence interval.

system model that is formulated as follows:

$$\begin{bmatrix} x(k+1) \\ d_r(k+1) \\ d_{s1}(k+1) \\ d_{s2}(k+1) \\ d_{s3}(k+1) \end{bmatrix} = \begin{bmatrix} A & BC_r & 0 & \dots & 0 \\ 0 & A_r & 0 & & \vdots \\ \vdots & 0 & A_{s1} & 0 & \vdots \\ \vdots & & 0 & A_{s2} & 0 \\ 0 & \dots & \dots & 0 & A_{s3} \end{bmatrix} \begin{bmatrix} x(k) \\ d_r(k) \\ d_{s1}(k) \\ d_{s2}(k) \\ d_{s3}(k) \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u(k) + w(k)$$

$$y_e(k) = \begin{bmatrix} C & 0 & C_{s1} & C_{s2} & C_{s3} \end{bmatrix} \begin{bmatrix} x(k) \\ d_r(k) \\ d_{s1}(k) \\ d_{s2}(k) \\ d_{s3}(k) \end{bmatrix} + Du(k) + v(k) \tag{4}$$

The notation $y_e(k)$ stands for the extended output. The main idea is to use an observer based on this extended system (4) to estimate the input and output disturbances d, and to use them in the MPC control law.

C. MPC Problem Formulation

Our implemented MPC algorithm is formulated based on the state-space model. Therefore, it uses the dynamic model of the oven (4), a *cost function* J over the receding horizon and quadratic programming (QP) algorithm to minimize J, taking explicitly into account the *constraints*. The following convex quadratic cost function used is given by

$$J = \sum_{i=H_w}^{H_p} \left\| \hat{y}_e(k+i|k) - r(k+i|k) \right\|_Q^2 + \sum_{i=0}^{H_u-1} \left\| \Delta u(k+i|k) \right\|_R^2 \tag{5}$$

where the variables $\hat{y}_e$ are the predicted controlled output, r is the reference trajectory and where $\Delta u(k) = u(k) - u(k-1)$. The parameter H_p is the prediction horizon, H_u is the control horizon, H_w is the "window" parameter and finally Q and R are constant weighting matrices. All of these parameters affect the behaviour of the closed-loop system composed by the plant and predictive controller. In (5) the weighted squared Euclidean norm is defined as $||x||_P^2 = x^T P x$ while the notation $(k+i|k)$ indicates that the involved variables depend on the conditions at time k. The MPC controller uses the model (4) to predict the behaviour of the plant, starting at the current time k, advancing on each point $k+i$ until reaching the future prediction horizon H_p. In addition, the cost function penalizes deviations of the predicted controlled outputs $\hat{y}_e$ from a reference trajectory r and changes of the incremental input vector Δu.

We imposed the following linear inequality constraints on control variables $u(k)$ and constrained outputs $y(k)_e$ at k-th step:

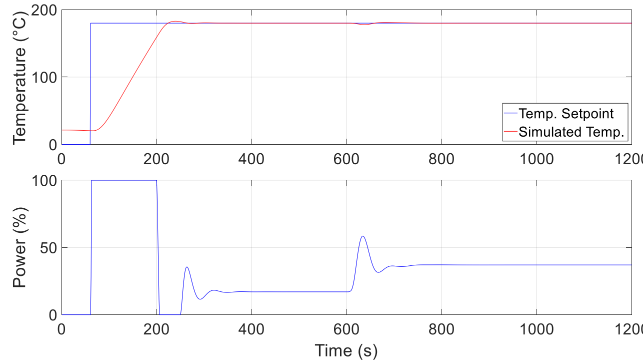

Fig. 6: The upper part of the figure shows the temperature regulation obtained by simulation; the blue signal in the lower part is the control input behaviour (step disturbance added @600s).

$$\Delta u_{min} \leq \Delta u(k) \leq \Delta u_{max} \tag{6a}$$
$$u_{min} \leq u(k) \leq u_{max} \tag{6b}$$
$$y_{min} \leq \hat{y}_e(k) \leq y_{max} \tag{6c}$$

The problem (5) was reformulated taking into account the constraints (6) as the following constrained optimization problem [10]:

$$\min_{\Delta U} \quad J = \Delta U(k)^T H \Delta U(k) - G^T \Delta U(k) \tag{7a}$$
$$\text{s.t.} \quad \Omega \Delta U(k) \leq \omega \tag{7b}$$

where ΔU is the control increment vector over the control horizon H_u. The Hessian matrix H is positive-definite because we imposed $Q \succeq 0$ and $R \succ 0$. The vector G depends on the tracking error between the future target trajectory and the free response of the system. The single inequality (7b) is the compact form of the inequalities (6a), (6b) and (6c) with Ω that represents a suitable selection of ΔU and ω is a function of the constraint limits, previous control variables $u(k-1)$ and the current system states $x(k)$. For more details on the mathematical steps, refer to [10].

Problem (7) is a convex optimization problem since we have the positive definite matrix H and the constraints (7b) that are linear inequalities. To solve this mathematical problem, a numerical optimization algorithm that is based on the Active-Set method [11] [12] was developed in order to be used in our prototype embedded system with limited hardware resources and to be executed in real time [18].

V. RESULTS

A. SIMULATION RESULTS

To validate the controller parameter setting and verify the feasibility of the proposed controller, numerical simulations were realized in the Matlab/Simulink development environment with the identified model as a plant. The characterization of the air flow generated by the fan is not considered in the simulation for the reasons aformentioned in Section IV-B. However, in the real use of the machine, it is present, thus this part will be dealt with in the experimental tests.

There are many adjustable parameters in the index performance (5) that must be set. Their tuning were based largely on experience gained from the simulations. The elements of

TABLE I: MPC control parameters values.

T_s	H_p	H_u	H_w	Q	R
1s	30	11	11	*diag*(10)	*diag*(0.01)

TABLE II: MPC control constraints values.

Δu_{min} %/s	Δu_{max} %/s	u_{min} %	u_{max} %	y_{min} °C	y_{max} °C
-20	80	0	100	0	250

R were decreased to obtain a fast response to compensate for the disturbances. On the other hand, the elements of Q were increased to penalize the tracking errors. The prediction horizon H_p was set greater than two times the number of states n to ensure that there are no "delayed modes" inside the controller which might emerge in the future [10]. The control horizon H_u and window parameter H_w were set to the number of states n, in order to have enough time to drive the controlled variable y to the reference r. Since there is a certain delay between the supply of heating energy and the observation of its effect, the parameter H_w is set at a value greater than one to avoid immediate penalizations of the deviations between the variables $\hat{y}$ and r.

Firstly, the cavity temperature is simulated using the model previously identified. The temperature is set to change from 20°C to 180°C and there is a step disturbance at 600 seconds, wherein, the simulation result is shown in Figure 6. Furthermore, the controller parameters after tuning are shown in Table I and the sampling interval of the simulation is 1 second. It can be observed that the proposed algorithm can track the temperature setting value with a small overshoot and almost with a zero steady state error. Meanwhile, the control variation Δu and u are kept within the range of the given constraints in Table II .

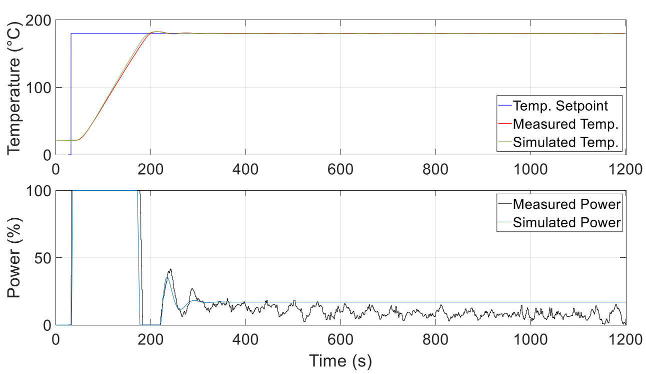

Fig. 7: Comparison between simulation and experiment results: on the top, the reference tracking performed by simulation (green) and prototype (red) is shown; on the bottom there is the comparison between the two control inputs.

B. EXPERIMENTAL RESULTS

After the tuning through simulation, the model predictive control has been implemented and evaluated in practice. We have implemented a hand-tailored QP algorithm written in the Matlab language, taking into account the computational and memory limitations of our embedded systems [18]. Furthermore, we have used the Embedded Coder which generates the C code from the Simulink diagrams, the Stateflow chart and the Matlab functions to our PLC platform. From Figure 7, the simulation and the prototype test can be compared. This test was carried out with a fixed rotation speed of the fan and the oven cell was empty. The control strategy in its complexity shows that it is able to describe the dynamics of the controlled plant. It also shows a good similarity with the simulation. Another comparison that can be made is between the performance of the MPC control and the current oven control. In Figures 8 and 9, the test that was carried out is for a setpoint of 180°C with a full load and the change of direction of the rotation of the fan is active. In the tests, there was a preheating phase without the load, in which the desired temperature was reached and then the load was introduced. In these tests we considered only the first 45 minutes after loading the cell.

TABLE III: The indicators for the control performance evaluation.

Performance index	Current Control	Proposed Control
Energy consumption (kJ)	28769	24702
Rise Time (s)	495	263
Overshoot (%)	5.55	2.11
Steady State error (°C)	3.75	0.65

As shown from the table above III, the new control consumes 14% less than the current control. It also takes about 230 seconds less to reach the setpoint. Also, the load disturbances attenuation with an increase of 82% can be seen when the oven is running in a steady state with the constant setpoint for a long period of time. Therefore, the new control action reduces spikes in the temperature profile, which significantly improves the average temperature regulation.

In Figures 11, 10 and 9, the performance of the MPC controller for a setpoint of 180°C with different loads are illustrated. The load we used to carry out the tests are trays made of "SAE 304" stainless steel. They are sealed on top with a lid of the same material. This lid is perforated to let the steam out. Each tray weighs around 500 grams and it was filled with 4 liters of water at room temperature. The tests were executed with the setpoint temperature higher than the boiling temperature of water to produce steam. According to the Figures 11, 10 and 9, it can be concluded that the temperature reference is reached while taking advantage of all the available input power and always considering its physical limitations. This is imposed in advance by the linear constraints on the control variable. Thus, a very short temperature rise time is achieved even despite different loads. While the command is within the saturation band, the control manages to compensate not only the energy absorption of the load and the heat loss but also the disturbance on the temperature measurement. With or without the presence of the

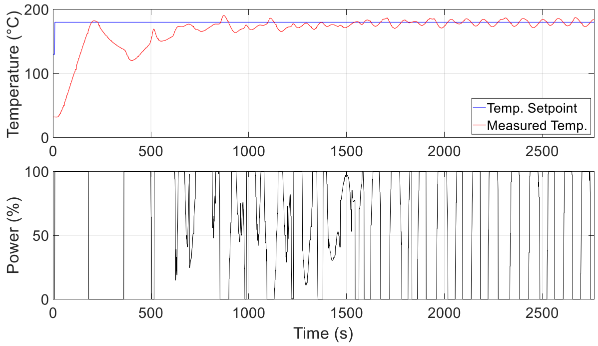

Fig. 8: The current oven control performance with full load (10 trays): the blue line is the temperature setpoint while the red line is the oven temperature signal; in black the power signal is shown.

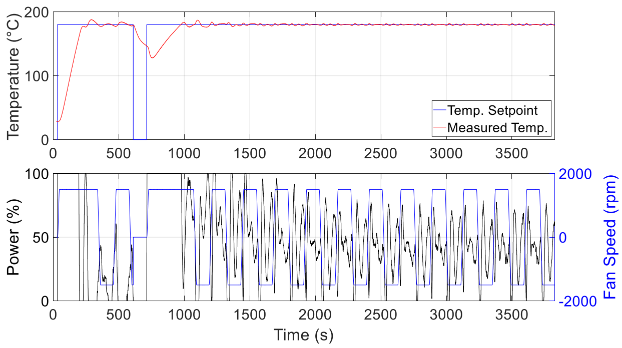

Fig. 9: The results of a test done with the proposed method (full load - 10 trays); the blue line is the temperature setpoint while the red line is the oven temperature signal; the lower part depicts the power command (black) and the fan speed (blue).

load in the tests, the control performance exhibits a similar and minute error in steady state. In this way, the quality and uniformity of cooking is guaranteed. Finally, the performance of this controller indicates that the tuning parameters are quite insensitive to the different test conditions.

VI. CONCLUSIONS

This work designed a model predictive controller for temperature control of the professional oven cavity. The proposed controller design flow adopts the subspace system identification method to identify the parameters of the model in state space formulation of the oven. It can be augmented with additional states to represent the disturbances present at the input and output of the system. The optimal command is found by solving a quadratic problem with linear constraints in real-time. The obtained performance of the new control system is highly satisfactory in regards to temperature homogeneity in the cell, setpoint deviation and energy consumption.

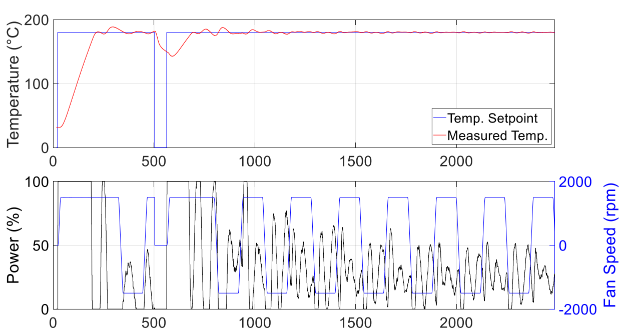

Fig. 10: The results of a test done with the proposed method (half load - 5 trays); the blue line is the temperature setpoint while the red line is the oven temperature signal; the lower part depicts the power command (black) and the fan speed (blue).

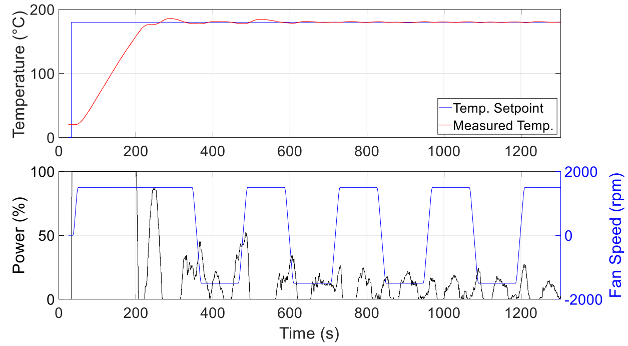

Fig. 11: The results of a test done with the proposed method (no load); the blue line is the temperature setpoint while the red line is the oven temperature signal; the lower part depicts the power command (black) and the fan speed (blue).

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