ON THE USE OF AN OFFLINE PID AND MULTIMODEL PREDICTIVE CONTROL APPROACH FOR DC-DC BOOST CONVERTER

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Abstract. *This paper focuses on investigating a new multi-model predictive control approach. The multi-model concept allows the representation of a nonlinear dynamic system as a combination of several linear models, each valid within specific operating zones. Based on a multi-model description, we propose a new design for multi-model predictive control. Our proposed control law synthesis consists in relying on a multi-model approach that combines an offline PID controller trained by neural network. To validate the effectiveness of our approach, a simulation study was conducted applying this control of a boost converter. The results demonstrate the suitability of our method for systems with rapid dynamics.*

***Keywords*: Multimodel, Predictive control, Fast dynamic systems, Boost converter**

1. INTRODUCTION

The multi-model approach has garnered significant attention since the publication of Johansen's work [1]. This approach involves apprehending the nonlinear behavior of a system through a collection of local models, which may be linear or affine, representing the system's functioning within distinct operating zones. This modeling approach is interesting since it offers on the one hand, a simplified and clear representation of the nonlinear model and on the other hand, to easily study the synthesis of the controllers. A particularly compelling aspect of the multi-model approach is its capability to enable the approximation of nonlinear systems through a weighted combination of local models using validity functions or membership criteria [2–4]. These validity functions somehow delimit the model's zone of action. Since a weighted sum of local models represents a nonlinear system, the idea is to use the same formalism for synthesizing the final control law with the local controllers.

Several works have been published from a predictive control perspective based on a multi-model representation [5–10]. The major interest of these approaches is manifested by the transformation of a nonlinear non convex optimization problem into a convex optimization one where its convergence is guaranteed. Adaptive structures as well as the study of stability have also been considered [11–13]. The development and availability of a mathematical model describing the dynamics of the system is a central subject in the strategy of predictive control. Nevertheless, the need for a nonlinear representation constitutes a great restriction at the practical level when one is confronted with fast dynamics systems. This is the problem of nonlinear and non-convex optimization. In this case, a modeling problem arises. Multi-models constitute a particular representation of nonlinear systems. Indeed, given a nonlinear system which has several operating points, by linearization we obtain as many local linear models. These local models are then interpolated to arrive at a linear multi-model, of which the dynamic model is an approximation of the nonlinear dynamics systems.

The organization of the article is as follows. Section 2 describes the new concept of multi-model predictive control strategy adopted. The implementation of the multi-model MPC algorithm to control a Boost converter is presented in section 3. Finally, a conclusion is given for the whole paper.

2. NEW CONCEPT FOR MULTIMODEL PREDICTIVE CONTROL

This method centers on nonlinear discrete single-variable systems described by a nonlinear input-output equation in the following forma t:

$$y(k) = f(y(k-i), u(k-j)), \forall i, j > 0 \tag{1}$$

Where $y(k) \in \Re$ represents the output of the system, $u(k) \in \Re$ is the manipulated variable and *f* is an application of $\Re \times \Re$ in $\Re$. The nonlinear process is represented by Volterra model. The parametric second-order discrete Volterra model has the following form :

$$y(k) = y_0 + \sum_{i=1}^{n_y} a_i y(k-i) + \sum_{i=1}^{n_u} b_i u(k-i) + \sum_{i=1}^{n_y} \sum_{j=1}^{i} b_{ij} u(k-i) u(k-j) + \varepsilon(k) \tag{2}$$

Where a_i, b_i represent the Volterra model parameters, and n_u, n_y are respectively the number of lags on the input and the output.

One advantage of the Volterra model is that it allows the one-ahead prediction problem to be framed as a linear regression, thus simplifying the parameter identification process from input-output data. Hence, the model represented in (2) can be expressed as:

$$y(k) = \theta^T \varphi(k) + \varepsilon(k) \tag{3}$$

With :

$$\theta^T = [y_0, a_1, a_2, \ldots, a_{n_y}, b_1, b_2, \ldots, b_{n_u}, b_{1,1}, \ldots, b_{n_u, n_u}] \tag{4}$$

$$\varphi^T(k) = [1, y(k-1), \ldots, y(k-n_y), u(k-1), \ldots, u^2(k-1), \ldots, u^2(k-n_u)] \tag{5}$$

In (3), $\varphi^T(k)$ represents the regressor, while θ denotes the parameter vector. This model is characterized by linearity in parameters, allowing for the identification of both regressors and parameters based on input-output data.

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The proposed control strategy in this work is presented in Fig. 1. This scheme focuses on model predictive control of nonlinear systems with fast dynamics, more precisely the synthesis of a new control strategy integrating the multimodel approach. In this work, the control is supposed to be composed of two levels: a global level and a local level.

- At the local level, several models each having a local objective. The set of local objectives can be grouped together to ensure a global performance.
- At the global level, an offline PID controller tuned by a neural network is used as a lookup table in the microcontroller taking into account the results of local objectives in terms of ensuring tracking, regulation performance and essentially the constrained $u(k)$ and $\Delta u(k)$.

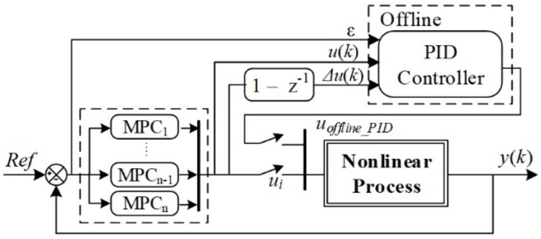

Fig. 1. Bloc diagram of Multimodel predictive control strategies

The optimization problem which is generally non-convex, is transformed on an explicit solution added to an offline PID, the consumption time calculation is reduced, in fact the nonlinear optimization is avoid. Added to that, the proposed technique which is presented and discussed can be applied to systems with dynamics rapid

3. LOCAL MULTIMODEL PREDICVE CONTROL

3.1. Model base construction

The number of models can determined by using both two algorithms: the Frequency Sensitive Competitive Learning (FSCL) and Fuzzy c-means [14–18]. The structure of each model's base is given by an ARX (AutoRegressive eXogenous) equation defined by :

$$y_i(k) = -\sum_{i=1}^{n_a} a_i y_i(k-i) + \sum_{j=1}^{n_b} b_j u_i(k-j) + c_i \tag{6}$$

The parameters a_i and b_i of the i[th] local model are determined through the Recursive Least-Square method during identification. The instrumental determinant ratio-test [19] is employed to estimate the order of each model base. Each local model i is described by a discrete model in the following form:

$$\begin{aligned} x_i(k+1) &= A_i x_i(k) + B_i u(k) + x_{i0} \\ y_i(k) &= C_i x_i(k) + y_{i0} \end{aligned} \tag{7}$$

Using $x_k \in \mathcal{R}^n$ to represent the state vector, $u_k \in \mathcal{R}^n$ as the control signal, $y_k \in \mathcal{R}^n$ as the output of the system, where A_i, B_i, C_i denote matrices of appropriate dimensions, while $x_{i0} \in \mathcal{R}^n$ and $y_{i0} \in \mathcal{R}^n$ signify the initial state-level and output-level offsets, respectively.

The multi-model representation is entrusted to a validity computation based on a residue approach. Residues are expressed by the difference between the output y of the system and elementary outputs y_i of each model. The residues are evaluated according to the following expression :

$$r_i = |y - y_i|,\ i = 1, 2, \dots, N_m \tag{8}$$

Where

N_m : Number of models in the base,

The multimodel output, represented as a validity combination, is given by [20, 21]:

$$y = \sum_{i=1}^{N_m} v_i y_i \tag{9}$$

Where

$$\begin{aligned} & v_i^{ref}(k) = v_i^{simp}(k) \prod_{j=1,\, j\neq i}^{N_m} \left(1 - v_j^{simp}(k)\right), && i = 1, 2, \dots, N_m \\ & v_i^{simp}(k) = \frac{1 - r_i^{norm}(k)}{N_m - 1}, && i = 1, 2, \dots, N_m \\ & r_i^{norm}(k) = \frac{r_i(k)}{\sum_{i=1}^{N_m} r_i(k)}, && i = 1, 2, \dots, N_m \\ & \sum_{i=1}^{N_m} v_i^{simp} = 1 \qquad \sum_{i=1}^{N_m} v_i^{ref} = 1 \end{aligned} \tag{10}$$

3.2. Local MPC

The solution of the local predictive control for each model corresponds to an explicit solution given by the minimization of this cost function :

$$J(H_p,H_u,R,Q)=\sum_{j=1}^{H_p}\left\|y_i(k+j|k)-y_{ref}(k+j)\right\|_Q^2+\sum_{j=0}^{H_u-1}\left\|u_i(k+j|k)\right\|_R^2 \tag{11}$$

The prediction of a local output is given by successive iteration of (7) according to :

$$y_i(k+j)=C_iA^jx_i(k)+\sum_{m=0}^{j-1}C_iA_i^{-1-m}(B_iu_i(k+m)+x_{i0})+y_{i0} \tag{12}$$

Taking into account (12), one can write the matrix equations describing the local predicted output. Indeed, if we define :

$$\begin{aligned}
Y_i(k)&=\left[\,y_i(k+1|k)\cdots y_i(k+H_p|k)\right]^T\\
U_i(k)&=\left[\,u_i(k)\cdots u_i(k+H_u-1)\right]^T\\
Y_{réf}(k)&=\left[\,y_{réf}(k+1|k)\cdots y_{réf}(k+H_p|k)\right]^T
\end{aligned} \tag{13}$$

Where

$$H_i=\begin{bmatrix} C_iB_i & \cdots & 0 & \cdots & 0\\ C_iA_iB_i & \cdots & C_iB_i & \cdots & 0\\ \vdots & \ddots & \vdots & \ddots & \vdots\\ C_iA_i^{H_p-1}B_i & \cdots & C_iA_i^{H_p-2}B_i & \cdots & C_i\sum_{m=H_u}^{H_p-1}A_i^{H_p-m-1}B_i \end{bmatrix}\quad \Gamma_i=\begin{bmatrix} C_iA_i\\ C_iA_i^2\\ \vdots\\ C_iA_i^{H_p}\end{bmatrix},\quad O_i=\begin{bmatrix} y_{i0}+Cx_{i0}\\ y_{i0}+CAx_{i0}\\ \vdots\\ y_{i0}+\sum_{m=0}^{H_p-1}C_iA_i^mx_{i0}\end{bmatrix} \tag{14}$$

The predicted local output is expressed by :

$$Y_i(k)=\Gamma_ix_i(k)+H_iU_i(k)+O_i \tag{15}$$

The cost function (11), is rewritten as :

$$J=(H_iU_i(k)+P_i(k))^T(H_iU_i(k)+P_i(k))+U_i(k)^TT_iU_i(k) \tag{16}$$

With :

$$P_i(k)=\Gamma_ix_i(k)+O_i-Y_{ref}(k) \tag{17}$$

The minimum of (17) is obtained if the gradient of J equals zero, resulting in the subsequent optimal solution :

$$U_i(k)=-(H_i^TH_i+R)^{-1}H_i^TP_i \tag{18}$$

To adhere to the restrictions placed on the command and its increment, we opt to confine the final solution, u_{mm}, within the permissible limits of $u_{\min}$ and $u_{\max}$. Additionally, the devised control, u_{sub}, is constrained by two thresholds that encompass both its maximum and minimum deviations. These thresholds are defined as :

$$\begin{aligned}
\lim_{\max}&=\min(u_{\max}-u(k-1),\Delta u_{\max})\\
\lim_{\min}&=\max(u_{\min}-u(k-1),\Delta u_{\min})
\end{aligned} \tag{19}$$

Where $\Delta u_{\max}$ and $\Delta u_{\min}$ are respectively upper and lower deviation of the control.

4. OFFLINE PID

The structure of PID controller, used offline, is given in Fig. 2.

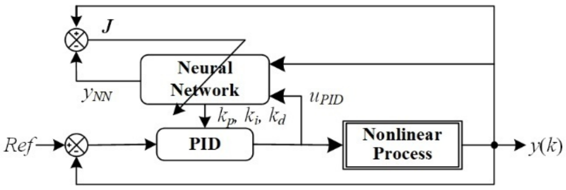

Fig. 2. Offline PID controller bloc diagram.

The used velocity of the PID controller is of the form :

$$u(k)=u(k-1)+k_p(e(k)-e(k-1))+k_ie(k)+kd(e(k)-2e(k-1)+e(k-2) \tag{20}$$

The PID controller's parameters k_p, k_i and k_d are tuned using an RBF neural network [22–26]. The neural network's offline performance index is defined as follows :

$$J=y(k)-y_{NN}(k) \tag{21}$$

Where $y(k)$ and $y_{NN}(k)$ are respectively the systems output and the network output. J is used to adjust the neural network weight according to the following equations :

$$\begin{aligned}
w_j(k)&=w_j(k-1)+\eta Jh_j+\alpha(w_j(k-1)-w(k-2)\\
b_j&=b_j(k-1)+\eta\Delta b_j+\alpha(b_j(k-1)-b_j(k-2)
\end{aligned} \tag{22}$$

Where h is the Gaussian activation function, η and α are respectively the learning rate and the momentum factor.

The final error of the neural network $e(k)$ is expressed by :

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$$e(k) = Ref(k) - y(k) \tag{23}$$

Using the gradient descent, the adjustment parameters of the PID controller are given by :

$$\begin{aligned}
\Delta k_p &= \eta e(k)\frac{\partial y}{\partial u}(e(k)-e(k-1)) \\
\Delta k_i &= \eta e(k)\frac{\partial y}{\partial u}(e(k)) \\
\Delta k_d &= \eta e(k)\frac{\partial y}{\partial u}(e(k)-2e(k-1)+e(k-2))
\end{aligned} \tag{24}$$

5. BOOST CONVERTER CONTROL STUDY

A Boost converter is employed in the novel implementation of multimodel predictive control. The block diagram is illustrated in Fig. 3.

This PWM signal controls the switching of the power transistor through the MOSFET driver. The boost output is connected to the input of the microcontroller's analog-to-digital converter (ADC). The system to be identified presents the following characteristics:

Supply voltage: $V_{DC} = 12V$,

Output voltage: $V_{out} = 24V$,

Hash frequency: *80kHz,*

Load resistance: $R_{ch} = 50\Omega$,

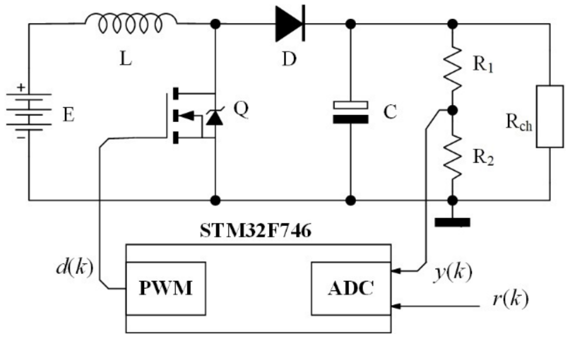

Fig. 3. Boost Converter bloc diagram

Several methods are used to identify system parameters. We prefer in this work an experimental approach to determine the nonlinear Volterra model transfer function of the system.

The identification test consists in generating an Amplitude-modulated Pseudo-Random Binary Sequence (APRBS) and applying it to the system's input [27].

The FSCL algorithm is employed to ascertain the appropriate number of clusters for multiple models. The outcomes are depicted in Fig. 4(a). Utilizing five neurons in the output layer, it's observed that two centers deviate from the data points. Thus, we infer that the optimal number of clusters is three. The classification outcomes are illustrated in Fig. 4(b). Subsequently, for each of the three data sets corresponding to the different clusters, the transfer function parameters and orders are estimated for the three base models. Employing the instrumental determinant ratio-test method reveals that the order of each model is two, while the Recursive Least-Squares method yields diverse transfer functions.

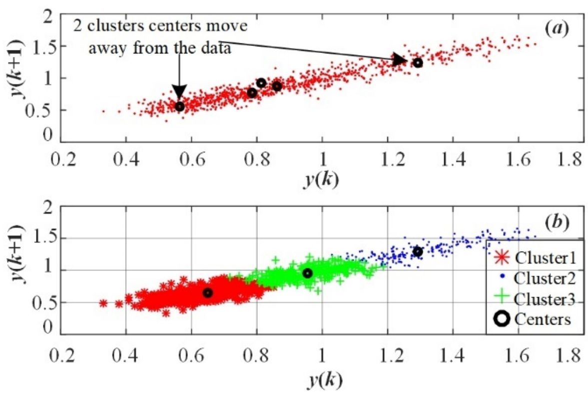

Fig. 4. Determination of the number of cluster (FSCL c=5) and clustering results (c=3)

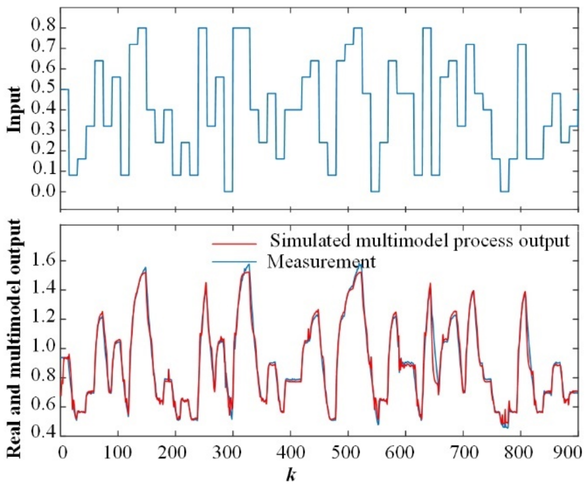

Fig. 5. Real and multimodel outputs

The proposed concept illustrated in Fig. 1 is applied to control an electrical process designed by a boost converter. At the same time, we use a nonlinear programming procedure to control the nonlinear process (NMPC). The results carried in Fig. 6 are used to compare both approaches, so it is clear that the proposed technique approved good control performances.

A comparative study between the proposed approach and the NMPC is also presented. We can notice first that there is no violation of the proposed constrained which are of the form : $0 < u(k) < 0.5$ and $|u(k)| < 0.05$. Second that the systems output converges quickly to the adopted reference. A Comparisons study between the two approaches is made. So for the proposed one we notice that:

■ The proposed approach achieves convex optimization in resolving the problem.

■ To verify if this the proposed approach is able to reject disturbances, we introduce an output disturbance at time points k = 250 and k = 700. Remarkably, the disturbance is successfully mitigated, demonstrating the strategy's capacity in disturbance rejection. Hence, it is proven that the applied control concept significantly enhances control performance.

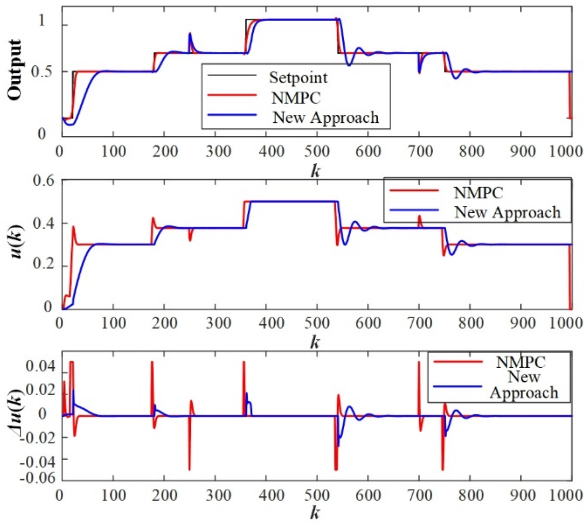

Fig. 6. Evolution of the output/setpoint and command signals : Proposed approach and NMPC

Fig. 7(a) illustrates the computation time required at each step for generating the sequence command, comparing both the new approach and the NMPC case. The proposed concept procured a significant reduction in complexity of calculation when we use an online nonlinear optimization procedure. The optimization challenge stands out as the most computationally intensive, showing the impracticality of real-time implementation in time-constrained systems. In Fig. 7(b), we illustrate the sampling intervals utilizing the PID solution stored in a lookup table. Out of 900 iterations, the PID controller solution was employed in only 35.56% of cases, demonstrating a significant 64.44% reduction in computational burden.

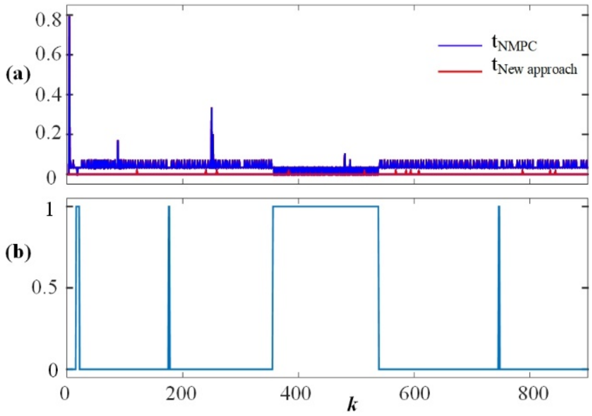

Fig. 7. Evaluation of the required implementation time (a). Instants of the use of the neural network (b)

By comparing the results, it becomes clear that the innovative control system exhibits markedly enhanced control efficacy when compared with a conventional NMPC setup. This avoids the challenge inherent in minimizing the performance function for nonlinear predictive control, a task typically addressed through nonlinear programming techniques solved at each sampling time, generally is non-convex. To compare the novel concept with the NMPC controller, a performance evaluation was conducted using the performance indices [28] given by :

$$SSE = \sum_{k=1}^{N}\left(y_{ref}(k) - y(k)\right)^2$$
$$SSU = \sum_{k=1}^{N}\left(u(k) - u(k-1)\right)^2 \tag{25}$$
$$SS\Delta U = \sum_{k=1}^{N}\Delta u^2(k)$$

In Table 1, SSE represents the sum of squared errors, SSU indicates the sum of squared control signals, SSΔU denotes the sum of squared changes in the control signal, and N signifies the number of samples. The data reveals that employing the NMPC controller significantly enhances control performance within the novel concept strategy. Furthermore, this method provides the best tracking performance and minimizes energy consumption.

Table 1. *Control performance comparison*

	SSE 10^{-8}	SSU 10^{-11}	SSΔU 10^{-11}
NMPC	5.4436	2.7052	3.9267
New approach	$1.009\text{x}10^{-5}$	$3.5770\text{x}10^{-5}$	$6.0565\text{x}10^{-6}$

6. CONCLUSION

Nonlinear model predictive control has long required for efficient diversity of process control in many industrial cases. Suffering from time consumption when used with fast dynamics systems as an alternative a modified multimodel predictive control is designed to control successfully a boost converter. The suggested approach demonstrates a favorable comparison when assessed alongside a numerical optimization routine. So, it avoids a nonlinear optimization procedure. Furthermore, the novel algorithm alleviates the online computational load, presenting promising prospects for application in systems characterized by swifter time constants. The computational demands in our approach are simpler and faster compared to nonlinear optimization, providing a good control performance

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