FINITE CONTROL SET MODEL-BASED PREDICTIVE CONTROL APPLIED TO A NON-EVENT BASED PROCESS

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Abstract— This paper proposes a study about finite control set model-based predictive control (FCS-MPC) applied to a non-event based process. A theoretical background is provided, presenting the pros and cons with this control technique. Some improvements for the conventional FCS-MPC are proposed, such as dynamic set range. Simulation results are presented to corroborate the developed theory.

Keywords— Predictive control, FCS-MPC, process control.

Resumo— Esse artigo propõe o estudo do controle preditivo baseado em modelo de conjunto de ações de controle finito applicado a um processo não baseado em eventos. Uma fundamentação teórica é fornecida, apresentando os prós e contras da técnica de controle. Algumas melhorias à estratégia convencional são propostas, como variação dinâmica do conjunto. Resultados de simulação são apresentados para corroborar a teoria desenvolvida.

Palavras-chave— Controle preditivo, FCS-MPC, controle de processos

1 Introduction

Finite control set model-based predictive control (FCS-MPC) is a particular class of model-based predictive control (MPC) that was developed in the power electronics field (Rodriguez et al., 2007; Rodriguez et al., 2013). Essentially, FCS-MPC technique and its variations are used to treat process with an event-based characteristics, as the commutated converters seen in power electronics, due to their intrinsic property to deal with a finite control action set (Vazquez et al., 2014; Vazquez et al., 2017).

Thus, FCS-MPC is characterized to have a countable, and usually finite and pretty limited, control set, that comprehends all possible control actions for the process. Therefore, FCS-MPC is in opposition to other MPC techniques, also called as convex control set model-based predictive control (CCS-MPC), which treat process with the entire real number set, or at least a constrained convex set, as control action possibilities (Bordons and Montero, 2015; Preindl, 2016).

In the power electronics field, the main advantage of FCS-MPC is its capability to treat directly the commutation nonlinearity instead of using a modulator (Young et al., 2014), which also implies problems as variable switching frequencies and higher total harmonic distortion rates (Vazquez et al., 2014). However, as other MPC techniques, FCS-MPC has the capability to treat process constraints in the control design and to handle with multi-variable problems in its formulation. In addition, FCS-MPC may have a significant lower computational burden if compared with other MPC techniques that treat process constraints (Bordons and Montero, 2015; Negri et al., 2017). It also can treats directly some process nonlinearities without linearization and allows to employ a significant variety of cost functionals. Indeed, FCS-MPC usually has small prediction horizons (about one or two steps ahead prediction), which reduces its computational burden (Mayne, 2014).

Although FCS-MPC is essentially related to process with finite control set, that are usually event-based, it is not necessarily restricted to them. It is possible to apply FCS-MPC to any process that could have its control set quantized (Aguilera and Quevedo, 2013). Therefore, it is possible to explore the benefits proportioned by it, as the treatment of process constraints with low computational burden, to almost every physical or industrial process. The main drawback is the switched control action, proportioned by this control, which could reduce process actuator life cycle and could propagate noise and internal resonances of the process and its sensors (Aguilera and Quevedo, 2013).

Other problems caused by the FCS-MPC are the non steady-state stabilization. This control technique stabilizes in a limit cycle. Due to this, in some cases, there is a steady-state error, with average value of the process output being different of the output reference (Lezana et al., 2009; Aguilera et al., 2013).

Therefore, this paper proposes an investigation of which is the use of FCS-MPC to control a fluid-flow process, a non intrinsic event-based process. A similar idea of an optimal switched control strategy was explored by (Kirk, 2004), in the context of pure optimal control instead of model-based predictive control.

Furthermore, a dynamic set range to reduce the problems caused due to cycle limit steady state and other minor improvements are proposed. Therefore, this paper main contributions are related to the application of FCS-MPC in a non event-based process, as the fluid-flow. Also, there is the presentation of three improvements for FCS-MPC algorithm considering its application in a non event-based process, and other minor improvements and analysis.

In Section 2, the process and the prediction are presented. The proposed control is presented in Section 3. The control design and simulation results are presented in Section 4. Finally, the conclusions and future works suggestion are exposed in Section 5.

2 Process and prediction model

The fluid-flow process to be controlled by FCS-MPC can be described as

$$\dot{x}(t) = f(x(t), u(t)) \tag{1}$$

being $x \in [0, x_{\max}]$ the state variable of process, in this case, the fluid level, $u \in [u_{\min}, u_{\max}]$ the control action, in this case, the voltage applied to the pump, $x_{\max}$ is maximum admissible value for $x(t)$ without the tank to overflow, $u_{\min}$ and $u_{\max}$ are the minimum and the maximum voltages admissible to be applied in the pump. The nonlinear relation f can be expressed with

$$f(x(t), u(t)) = -\frac{a}{A}\sqrt{2gx(t)} + \frac{k}{A}u(t) \tag{2}$$

where A is the cross section of tank, a is the cross section of the outlet hole, g is the gravity acceleration and k is the flow rate per voltage constant.

In order to obtain a prediction model for the control, it is necessary to discretize the nonlinear dynamics of the process. A possible alternative is the Euler discrete approximation, which, given a sampling period T_s, yields

$$x(t_k + 1) = f_k(x(t_k), u_k(t_k)), \tag{3}$$

where $u_k \in \mathbb{U}_k \subset [u_{\min}, u_{\max}]$ is the quantized control action, with n_s states, and

$$f_k(x(t_k), u(t_k)) = a_k\sqrt{x(t_k)} + b_k u_k(t_k)$$

being

$$\begin{aligned} a_k &= \left(1 - \frac{a}{A}\sqrt{2g}T_s\right), \\ b_k &= \frac{k}{A}T_s, \\ u_k &\in \{u_1, u_2, \ldots, u_{n_s}\}. \end{aligned}$$

3 Proposed control theoretical background

In this paper, the FCS-MPC use is being studied. However, some improvements are being proposed. Therefore, this section presents the fundamentals of MPC, the conventional FCS-MPC algorithms, found in the literature, and, specifically, each improvement in other subsections.

3.1 Fundamentals of MPC

MPC is a class of a large group of algorithms with similar properties among them (Qin and Badgwell, 2003; Mayne, 2014).

Essentially, a MPC algorithm solves an open-loop finite horizon N optimization problem (usually, the minimization of a cost functional J), subject to a prediction model and, possibly, terminal equality constraints and process inequality constraints (Mayne et al., 2000). Since the finite horizon optimization problem is solved, only the first term of the solution sequence also called optimal sequence

$$U_k^\star = \{u_k^\star(t_k), u_k^\star(t_k+1), \ldots, u_k^\star(t_k+N-1)\} \tag{4}$$

is applied to the process. Then, all the optimization problem is solved again in the next sampling time. This process is called receding horizon (García et al., 1989).

The horizon of an optimization problem is defined as the number of future evaluated cost functional samples, due to the predicted samples of the prediction model. This horizon is also known as prediction horizon N, in MPC literature (Mayne et al., 2000).

3.2 Conventional FCS-MPC algorithms

The conventional FCS-MPC algorithm, as presented in (Rodriguez et al., 2007; Rodriguez et al., 2009), assuming prediction horizon $N = 1$, consists in

1. Measure $x(t_k)$;
2. Set $J_{\min} \leftarrow \infty$;
3. For $i \leftarrow 0$ to n_s:
    (a) Calculate $x(t_k + 1)$ due to u_i applied in t_k;
    (b) Evaluate the cost functional J;
    (c) If $J < J_{\min}$:
        i. $J_{\min} \leftarrow J$;
        ii. $i_{\min} \leftarrow i$;

4. Set $u_k(t_k) = u_k^\star(t_k) \leftarrow u_{i_{\min}}$;
5. Wait the next sampling time;

Many times, due to the lower sampling times of power electronics, the main FCS-MPC algorithm is adapted (Aguilera et al., 2013), assuming prediction horizon $N = 2$, being employed as

1. Measure $x(t_k)$;
2. Set $u_k(t_k+1) = u_k^\star(t_k+1) \leftarrow u_{i_{\min}}$;
3. Estimates $x(t_k+1)$ due to $u(t_k+1) = u_{i_{\min}}$ and $x(t_k)$;
4. Set $J_{\min} \leftarrow \infty$;
5. For $i \leftarrow 0$ to n_s:
   (a) Calculate $x(t_k+2)$ due to u_i applied in t_k+1;
   (b) Evaluate the cost functional J;
   (c) If $J < J_{\min}$:
      i. $J_{\min} \leftarrow J$;
      ii. $i_{\min} \leftarrow i$;
6. Wait the next sampling time;

3.3 Dynamic set range

The dynamic set range consists in change the evaluated control action set $\mathbb{U}_k$ according to process current conditions. Since the evaluated process is not intrinsic event-based, it is possible to change, even dynamically, the $\mathbb{U}_k$ elements. These elements are only an extra control design resource and, therefore, can be chosen by the control designer. Considering the exposed before, some methods for dynamic set range evaluation are proposed.

3.3.1 Fixed set with dynamic search (FSDS)

The first idea consists in the use of a search horizon N_s. Given a large number of states n_s possibilities, the search horizon concept is a fixed, or variable, search horizon that evaluates the control actions based on the current control action. The search is performed according the following algorithm (other parts, involving measurement *et cetera*, are omitted):

1. Define $n_s \gg N_s$;
2. $i_0 \leftarrow i_{\min} - N_s$;
3. If $i_0 < 0$:
   (a) $i_0 \leftarrow 0$;
4. $i_f \leftarrow i_{\min} + N_s$;
5. If $i_f > n_s$:
   (a) $i_f \leftarrow n_s$;
6. For $i \leftarrow i_0$ to i_f:
   (a) Predict x due to u_i;
   (b) Evaluate the cost functional J;
   (c) If $J < J_{\min}$:
      i. $J_{\min} \leftarrow J$;
      ii. $i_{\min} \leftarrow i$;

The number of evaluations, in the worst case, is $2N_s + 1$ searches, with the approach presented before. High N_s values imply higher computational loads for the algorithm.

3.3.2 Fixed set with dynamic subset (FSDSs)

A second idea for the dynamic set is to use a fixed values set with larger voltage steps. Furthermore, a second set, called as dynamic subset, could be calculated considering the range between the voltages previously chosen by the controller. This approach is useful to reduce the oscillations in the control action and in the output. A possible algorithm (which is not the most optimized, but one of the simplest) to proceed with this strategy is:

1. Define n_s;
2. $i_{\min,\text{ant}} \leftarrow i_{\min}$;
3. If $(i_{\min,\text{ant}} > 0)$ and $(i_{\min,\text{ant}} < n_s)$:
   (a) Define $n_{s,b}$;
   (b) $u_{k,\max}(t_k) \leftarrow u_{i_{\min,\text{ant}}+1}$;
   (c) $u_{k,\min}(t_k) \leftarrow u_{i_{\min,\text{ant}}-1}$;
   (d) $du \leftarrow (u_{k,\max} - u_{k,\min})/n_s$;
   (e) $i \leftarrow 0$;
   (f) $du_i \leftarrow u_{k,\min}$;
   (g) While $i < n_{s,b}$:
      i. $u_{b,i} \leftarrow du_i$;
      ii. $du_{i+1} = du_i + du$;
      iii. $i \leftarrow i + 1$;
4. Proceed the first search (in u_i);
5. If $(i_{\min,\text{ant}} > 0)$ and $(i_{\min,\text{ant}} < n_s)$:
   (a) Proceed the second search (in $u_{b,i}$);

3.3.3 Dynamic set with control reference (DSCR)

Other dynamic set idea is to rearrange the limits, considering to use an reference value to the control action u_k^*. After that, it is possible to delimit a set based in other criteria, as the tracking error (converted to the control unity). The reference value could be obtained from the expected value for $u(t)$ in the steady state, associated to an integral effect to deal with model displacements. An approach similar to the proposed is explored by (Wang et al., 2016), that uses a dead-beat controller to guide the FCS-MPC. This work differs since it is proposed a dynamic set, generated by the control reference. In the previous work, the set was fixed and the control reference was used to reduce the search algorithm. A possible algorithm to establish the dynamic set is:

1. $e(t_k) \leftarrow x^*(t_k) - x(t_k)$
2. $e_a(t_k) \leftarrow e(t_k) + e_a((t_k) - 1)$;
3. $u_k^*(t_k) \leftarrow a\sqrt{2g}/kx^*(t_k) + e_a(t_k)$;
4. If $u_k^*(t_k) > u_{\max}$:
   (a) $u_k^*(t_k) \leftarrow u_{\max}$;
5. If $u_k^*(t_k) < u_{\min}$:
   (a) $u_k^*(t_k) \leftarrow u_{\min}$;
6. $u_{k,\text{amp}}(t_k) \leftarrow n_e|e(t_k)|u_{\max}/x_{\max}$

7. $u_{k,\max}(t_k) \leftarrow u_k^*(t_k) + u_{k,\text{amp}}(t_k)$
8. If $u_{k,\max}(t_k) > u_{\max}$:
   (a) $u_k^*(t_k) \leftarrow u_{\max}$;
9. $u_{k,\min} \leftarrow u_k^* - u_{k,\text{amp}}$
10. If $u_{k,\min}(t_k) < u_{\min}$:
   (a) $u_{k,\min}(t_k) \leftarrow u_{\min}$;
11. $du \leftarrow (u_{k,\max} - u_{k,\min})/n_s$
12. $i \leftarrow 0$
13. $du_i \leftarrow u_{k,\min}$
14. While $i < n_s$:
   (a) $u_i \leftarrow du_i$
   (b) $du_{i+1} = du_i + du$
   (c) $i \leftarrow i + 1$

It is important to note that in this approach the search horizon N_s is equal to the desired number of states n_s.

4 Control design and simulation results

The evaluated fluid-flow process has $A = 5$ cm^2, $a = 0.71$ cm^2, $g = 981$ cm/s^2, $k = 2$ cm^3/(Vs), $u_{\max} = 24$ V and $u_{\min} = 0$ V. The maximum safe tank level $x_{\max}$ is 1.6 cm (achieved with 24 V applied to the pump). The pump voltage dead zone nonlinearity is neglected. The established sampling time $T_s = 0.01$ s is sufficiently small if compared with process open-loop and closed-loop dynamics.

All tests were performed in 6 s of total simulation time. The level references were 0.8 cm from 0 to 2 s, 0.3 cm from 2 s to 4 s and 1.2 cm from 4 s to 6 s.

Several controllers were designed to explore different resources of the proposed technique. They are presented in the next subsections as well their closed-loop simulation results.

4.1 Fixed set with dynamic search results

The first results were obtained with the FDSD approach. The employed cost functional was:

$$J(x(t_k), u_k(t_k)) = \frac{1}{x_{\max}^2}(x^*(t_k+1) - x(t_k+1))^2 + J_{\text{const}} \quad (5)$$

assuming that $x^*(t_k+1) = x^*(t_k)$, $x(t_k+1)$ could be calculated using (3) and J_{const} given by

$$J_{\text{const}} = \begin{cases} \mu_c(x_{\max} - x(t_k+1)), & x(t_k+1) > x_{\max} \\ 0, & x(t_k+1) \leq x_{\max} \end{cases} \quad (6)$$

is the limitation cost, associated with the soft-constraint treatment of FCS-MPC (Preindl and Bolognani, 2013). In all tests performed the limitation weighting was $\mu_c = 10000$.

Figure 1 presents the results for the fixed set with dynamic search approach for prediction horizon $N = 1$ step ahead, $n_s = 120$ states and $N_s = 20$ states (Test 01). Figure 2 presents the results for the fixed set with dynamic search approach for prediction horizon $N = 3$, considering that the cost functional penalizes each prediction step, $n_s = 120$, $N_s = 8$ (Test 02).

As can be seen in Figures 1 and 2, the FSDS approach for FCS-MPC is capable to control the fluid-flow process suitably. An important fact is the relatively low control action ripple, which would be expected for a FCS-MPC given the switched nature of the control. The low ripple was a direct consequence from the FSDS approach, which works with a large number of states, ensuring a refinement in the applied voltage. The larger prediction horizon reduces some output peaks. However, overall, a larger N_s is preferable instead a larger N. A larger N causes a huge increase in the computational burden in comparison to a larger N_s. Nevertheless, a significant dynamic performance improvement is not observed.

4.2 Fixed set with dynamic subset results

The FSDSs approach tests were performed using the same cost functional from the FSDS approach, presented in (5).

Figure 3 presents the Test 03 performed with $n_s = 13$ and $N = 1$. In this test, no subsets were employed, which could be characterized as a conventional FCS-MPC approach (some discrete states evaluated one step ahead). Figure 4 presents the Test 04 performed with $n_s = 13$, $n_{s,b} = 10$ and $N = 1$. In the Test 04, only one dynamic subset was employed.

As observed in Figures 3 and 4, the use of a dynamic subset reduces significantly the control action ripple. Since in the Test 03 there is not a dynamic subset, but a pure FCS-MPC, and in the Test 04 there is the dynamic subset, the improvement is clear, besides being greater than the observed FDSD approach. The main advantage for the FSDSs approach, in relation to the FSDS one, is the considerably small n_s, which means low memory space to store the control actions states.

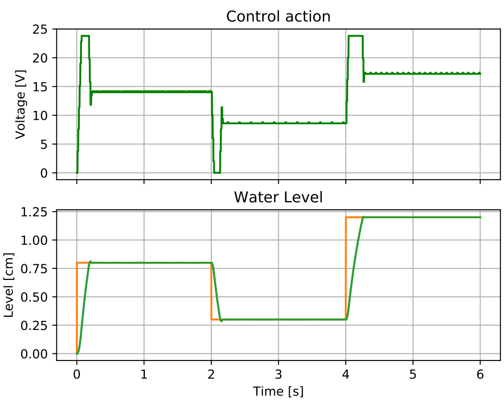

Figure 1: Results from Test 01

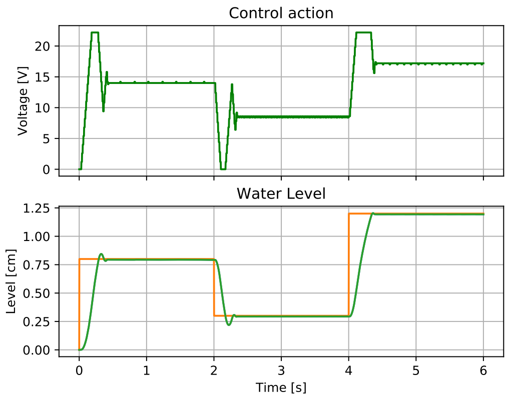

Figure 2: Results from Test 02

Other benefit from this approach is the faster transient, since all states from the main $\mathbb{U}_k$ are tested in all control evaluations. On the other hand, this strategy has a higher computational cost, considering that the subset is calculated dynamically and the number of searches could be higher than in the FSDS approach (since at least two searches are required).

4.3 Dynamic set with control reference results

The last approach tested was the DSCR approach. Figure 5 presents the Test 05 results, obtained from $n_s = 20$, $N = 1$ and $n_e = 15$. The same cost functional described by (5) was evaluated.

As seen in Figure 5, the DSCR has a lower control ripple if compared with the previous strategies, specially the FSDSs. The dynamic response is as faster as FSDSs. These positive aspects occur due to the unfixed states idea, that calculates the a new $\mathbb{U}_k$ at each sampling time, given the u_k^* existence. The error dependence in the $\mathbb{U}_k$ building guarantees well spaced u_k with large errors and near located u_k with small errors. Figure 6 allows to explore these concepts. It shows some elements from $\mathbb{U}_k$, in other words, some of

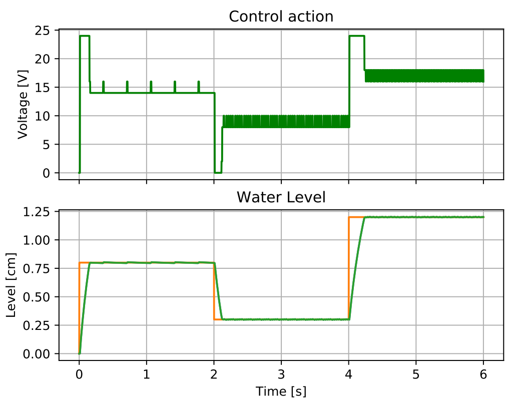

Figure 3: Results from Test 03

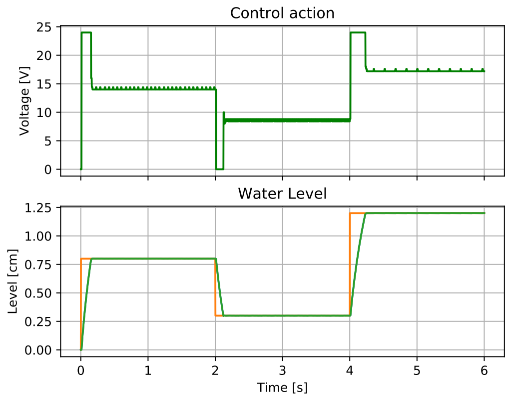

Figure 4: Results from Test 04

the twenty possible u_k in the time. It also shows u_k^*. In Figure 6, it is possible to see that when the error is large, the possible choices for u_k are more spaced. In other hand, when the error is small, the u_k are near each other, reducing the voltage ripple.

4.4 Stochasticity evaluation

In this subsection, a stochasticity evaluation of DSCR approach is presented to explore some possibilities of FCS-MPC. One of the main advantages of this control strategy is the flexibility with relation to the cost functional. Usually, fluid-flow processes have high noise level in the output measure. Therefore, a random noise, with maximum amplitude equal to 0.25 cm, was imposed to the output measurement and DSCR approach was applied as described in the Subsection 4.3. The result of this Test 06 is presented in Figure 7. As this figure shows, the control algorithm causes a huge noise propagation, spending a large control effort to maintain the output following the reference.

To reduce this large control effort, two alternative functional costs were proposed to be eval-

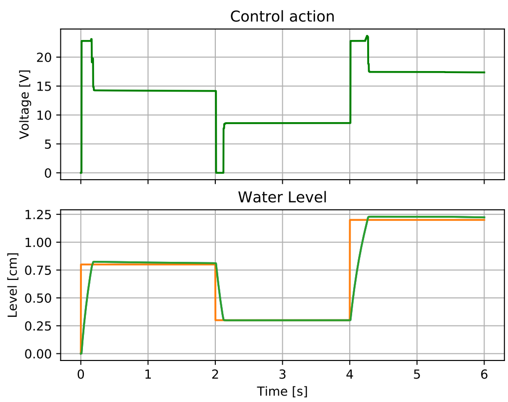

Figure 5: Results from Test 05

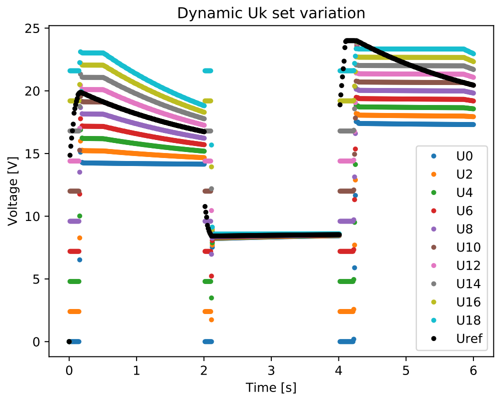

Figure 6: $\mathbb{U}_k$ set dynamic variation in Test 05

uated by the control algorithm.

The first functional is described by

$$\begin{aligned} J_1(x(t_k), u_k(t_k)) = & \frac{1}{x_{\text{max}}^2}(x^*(t_k+1) - x(t_k+1))^2 \\ & \frac{\mu_v}{u_{\text{max}}^2}(u_k(t_k+1) - u_k(t_k))^2 \\ & + J_{\text{const}}, \end{aligned} \tag{7}$$

where μ_v is the control variation weighting factor, tuned empirically.

Therefore, the functional described by (8) also penalizes the control effort variation. Considering $\mu_v = 0.1$, $n_s = 20$ and $n_e = 15$, Figure 8 presents the Test 07. It is possible to notice a significant reduction of the control effort to the control action, for obtaining almost the same, although slower, output response. Thus, for example, one advantage of the flexibility of FCS-MPC approach is the capability of obtaining minimum variance control characteristics, reducing the noise influence. These results could be improved if a stocastic model was employed as prediction model.

A second possible way to reduce control effort in the proposed FCS-MPC approach is to penalize

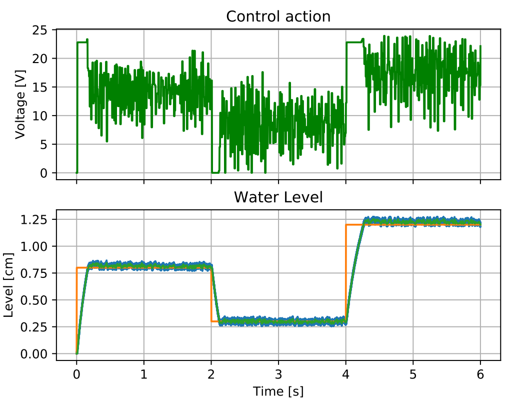

Figure 7: Results from Test 06

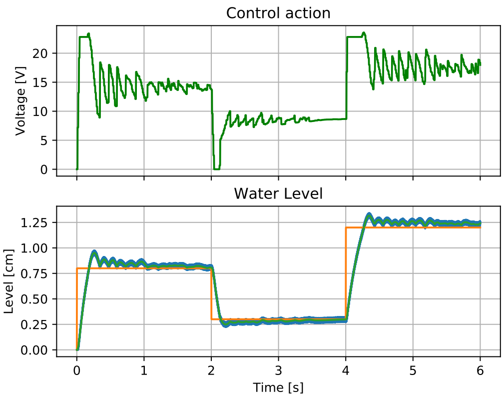

Figure 8: Results from Test 07

the distance to $u_k^*(t_k)$ in the cost functional, as

$$\begin{aligned} J_1(x(t_k), u_k(t_k)) = & \frac{1}{x_{\text{max}}^2}(x^*(t_k+1) - x(t_k+1))^2 \\ & \frac{\mu_v}{u_{\text{max}}^2}(u_k(t_k+1) - u_k^*(t_k))^2 \\ & + J_{\text{const}}. \end{aligned} \tag{8}$$

In this approach, smooth responses are obtained as it is possible to see in Figures 9 and 10, referred to Test 08 ($\mu_v = 0.01$, $n_s = 20$ and $n_e = 15$) and Test 09 ($\mu_v = 0.05$, $n_s = 20$ and $n_e = 15$), respectively.

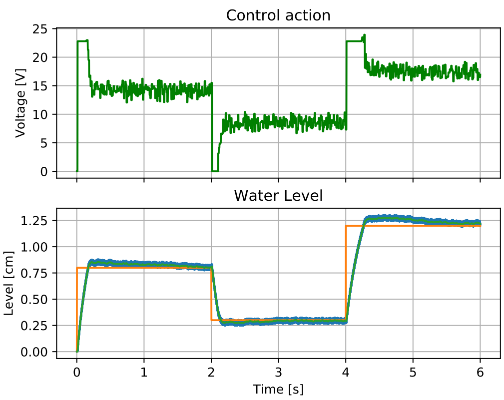

Figure 9: Results from Test 08

According to the μ_v tuning, it is possible to get a smoother, but slower response. Compared to the previous approach, the control effort variation is higher in frequency and smaller in amplitude. It occurs since the control action is concentrated around $u_k^*(t_k)$.

5 Conclusion

This paper proposed the application of FCS-MPC in a non event-based process, with some improvements to reduce the inherent voltage ripple of

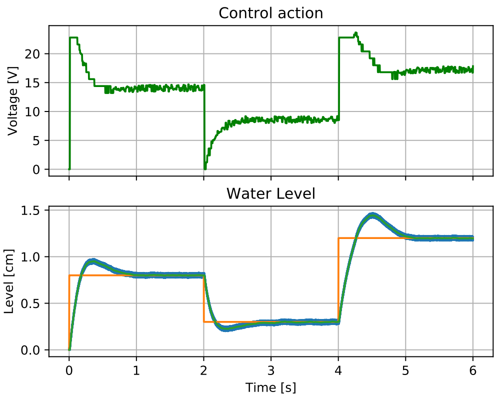

Figure 10: Results from Test 09

FCS-MPC. A case study is performed with a fluid-flow process, which is nonlinear, and the control algorithm was capable to guide the output to the reference. Among the improvements to FCS-MPC, the FSDS is the simplest, but still effective strategy. However, this approach uses a significant memory space and has a slower output response. The FSDSs approach presents a faster output response, with a higher computational burden than FSDS one and significant less memory space storage. The DSCR approach is more effective due to the complete dynamic variation of the control set, having lower voltage ripple if compared to previous approaches, but a higher computational load. A stochasticity evaluation was also explored for the DSCR case and it shows the flexibility of FCS-MPC, in this case, to include minimum variance control properties. Two possibilities are given and both are effective being, one to reduce the control ripple frequency and other to reduce the control ripple amplitude.

Thus, it is possible to conclude that FCS-MPC is a good alternative to control nonlinear non event-based processes, specially, with the improvements presented in this paper. It main advantage is it flexibility to evaluate the suitable cost functional for the process, also treating the process constraints, with a low computational burden if compared with other nonlinear model-based predictive controllers.

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References

Aguilera, R. P., Lezana, P. and Quevedo, D. E. (2013). Finite-control-set model predictive control with improved steady-state performance, *IEEE Transactions on Industrial Informatics* **9**(2): 658–667.

Aguilera, R. P. and Quevedo, D. E. (2013). Stability analysis of quadratic MPC with a discrete input alphabet, *IEEE Transactions on Automatic Control* **58**(12): 3190–3196.

Bordons, C. and Montero, C. (2015). Basic principles of MPC for power converters: Bridging the gap between theory and practice, *IEEE Industrial Electronics Magazine* **9**(3): 31–43.

García, C. E., Prett, D. M. and Morari, M. (1989). Model predictive control: Theory and practice — a survey, *Automatica* **25**(3): 335–348.

Kirk, D. E. (2004). *Optimal Control Theory*, Dover Publications.

Lezana, P., Aguilera, R. and Quevedo, D. (2009). Steady-state issues with finite control set model predictive control, *2009 35th Annual Conference of IEEE Industrial Electronics*, pp. 1776–1781.

Mayne, D. Q. (2014). Model predictive control: Recent developments and future promise, *Automatica* **50**(12): 2967–2986.

Mayne, D., Rawlings, J., Rao, C. and Scokaert, P. (2000). Constrained model predictive control: Stability and optimality, *Automatica* **36**(6): 789 – 814.

Negri, G. H., Cavalca, M. S. M., de Oliveira, J., Araújo, C. J. F. and Celiberto, L. A. (2017). Evaluation of nonlinear model-based predictive control approaches using derivative-free optimization and FCC neural networks, *Journal of Control, Automation and Electrical Systems* **28**(5): 623–634.

Preindl, M. (2016). Robust control invariant sets and lyapunov-based MPC for IPM synchronous motor drives, *IEEE Transactions on Industrial Electronics* **63**(6): 3925–3933.

Preindl, M. and Bolognani, S. (2013). Model predictive direct speed control with finite control set of PMSM drive systems, *IEEE Transactions on Power Electronics* **28**(2): 1007–1015.

Qin, S. J. and Badgwell, T. A. (2003). A survey of industrial model predictive control technology, *Control Engineering Practice* **11**: 733–764.

Rodriguez, J., Cortes, P., Kennel, R. and Kazrnierkowski, M. P. (2009). Model predictive control - a simple and powerful method to control power converters, *2009 IEEE 6th International Power Electronics and Motion Control Conference*.

Rodriguez, J., Kazmierkowski, M. P., Espinoza, J. R., Zanchetta, P., Abu-Rub, H., Young, H. A. and Rojas, C. A. (2013). State of the art of finite control set model predictive control in power electronics, *IEEE Transactions on Industrial Informatics* **9**(2): 1003–1016.

Rodriguez, J., Pontt, J., Silva, C. A., Correa, P., Lezana, P., Cortes, P. and Ammann, U. (2007). Predictive current control of a voltage source inverter, *IEEE Transactions on Industrial Electronics* **54**(1): 495–503.

Vazquez, S., Leon, J. I., Franquelo, L. G., Rodriguez, J., Young, H. A., Marquez, A. and Zanchetta, P. (2014). Model predictive control: A review of its applications in power electronics, *IEEE Industrial Electronics Magazine* **8**(1): 16–31.

Vazquez, S., Rodriguez, J., Rivera, M., Franquelo, L. G. and Norambuena, M. (2017). Model predictive control for power converters and drives: Advances and trends, *IEEE Transactions on Industrial Electronics* **64**(2): 935–947.

Wang, Y., Niimura, N. and Lorenz, R. D. (2016). Real-time parameter identification and integration on deadbeat-direct torque and flux control (DB-DTFC) without inducing additional torque ripple, *IEEE Transactions on Industry Applications* **52**(4): 3104–3114.

Young, H. A., Perez, M. A., Rodriguez, J. and Abu-Rub, H. (2014). Assessing finite-control-set model predictive control: A comparison with a linear current controller in two-level voltage source inverters, *IEEE Industrial Electronics Magazine* **8**(1): 44–52.