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Optimization of Product Grade Transition by Model Predictive Control

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ABSTRACT

The production of synthetic polymers represents an important part of chemical industry. In these processes it is common that the same process is used for the production of different kind of products (various molecular weights, compositions, etc.). Therefore, beside the optimization of the operating conditions related to the production of different products, it is also important to minimize the time of the grade transition reducing the amount of off-specification products. This optimization can be considered as an optimal control problem. Among the wide range of tools and algorithms can be used to solve optimal control problems this paper studies the applicability of model predictive control (MPC) solutions. In the chemical industry the influence of MPC is increasing, they are very successful in wide range of industrial applications. This became possible because more and more algorithms are available for the implementation of model predictive controllers. MPC requires a proper model for the prediction of the effect of the current control signal to allow its optimization. It is important to note that the nonlinear behavior of the process mainly appears during grade transitions than at steady state operation. This phenomena would require the utilization of nonlinear models in the controller. However, the application of nonlinear first-principles models is restricted due to the formulation of these models requires the identification of large amount of kinetic parameters, which can be very time-consuming and costly. In these situations the applications of data-driven models models could be more beneficial. Hence this paper MPC solutions for the optimization of grade transitions based on input/output data driven models is studied. The free radical polymerization reaction of methyl-metacrylate is considered using azobisisobutironitil (AIBN) as initiator, and toulene as solvent. The aim of the process is producing different kind of grades, and the number-average molecular weight was for identify the right state of process, and it can be influenced by the inlet initiator flow rate. The proposed controller is compared to the wide-spread applied PID controllers and the control performances results are qualified the ISE (integral Square of Error) criteria. Using the impulse response and the step response models of the reactor, Dynamic Matrix Controller as MPC has been designed. The results show that the performance of the model predictive controller is better than the performance of PID controller which is also proved by the ISE criteria.
(Keywords: MPC, predictive control, polymerization, impulse response)

ÖSSZEFOGLALÁS

Termékváltás optimalizálás modell prediktív szabályozók segítségével
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A szintetikus polimerek előállítása fontos részét képezi a vegyiparnak. Gyakori, hogy ugyanazt a folyamatot alkamazzák különböző termékek előállítására (különböző átlagos

molekulatömeg, összetétel, stb). Különböző termékekhez kapcsolódó gyártási feltételek optimalizálása mellett azonban fontos, hogy a termékváltások közti ún. off-grade termékek mennyiségét minimalizálják. A termekváltás optimálása egy optimális irányítási feladatnak tekinthető. A széles körben alkalmazott eszközök és algoritmusok, amik optimális irányítási feladat megoldására irányulnak, közül a model prediktív szabályozókat (MPC) kiválasztva azoknak az alkalmazhatóságának vizsgálatára került sor. Az iparban az MPC megoldások alkalmazása egyre terjed, széles körben való alkalmazhatóságuk miatt. Az MPC-hez szükséges egy megfelelő modell, aminek segítségével a pillanatnyi beavatkozó jel hatása előrejelezhető, ami lehetővé teszi az optimalizálást. A polimerizációs reaktorok nem lineáris viselkedése főként termékváltásoknál jelenik meg, ezért pontos modell az egész terméksálára vonatkozóan nehezen készíthető. A fehér doboz modellek készítése megodást jelenthet a nemlináris viselkedés leírására, azonban a szükséges kinetikai paraméterek nehezen és költségesen hozzáférhetőek. Ezért adatgyűjtésen-identifikáláson alapuló fekete doboz modellek használata megoldást jelenthet, ahogyan ebben a tanulmányban is bemenet-kimenet pontpárokon alapuló fekete doboz modellt alkalmazására került sor. A lejátszódó folyamat egy gyökös polimerizációs folyamat, aminek a terméke poli-metil metakrilát. A termék azobisz-izobutironitril iniciátor hatására toluol oldószeres környezetben keletkezik. A cél különböző polimetil-metakrilát termékekek előállítása. A termékek az átlagos molekultömegükkel jellemezhetőek, ami az iniciátor adagolásával befolyásolható. A tervezett model prediktív szabályozót összehasonlítottuk a széles körben alkalmazott PI szabályozóval a teljeítményük alapján, ami az ISE kritérium alapján számszerűsthető. A reaktor súlyfüggvényén és átmeneti függvényén alapuló konvulúciós modellt felhasználva készíthettünk egy dinamikus mátrix szabályozót (DMC). Az eredmények alapján, amit szintén az ISE kritérium mutat, belátható, hogy a DMC szabályozó jobb teljesítménnyel rendelkezik.
(Kulcsszavak: MPC, prediktív irányítás, polimerizációs technológiák, konvolúciós modell)

INTRODUCTION

The production of the synthetic polymers represents an important part of chemical industry. In this industrial segment one reactor is usually used for producing different kind of products (various molecular weights, compositions, etc.).

During transitions between products, so-called off-spec products are produced. This product is generally worth less than the on-spec material; therefore it is of interest to minimize its production. The on-spec material can be produced under varying circumstances and at varying operating points, which are more or less economically sound, motivating optimization of the production during production stages.

In these processes a large number of different grades are produced, and the transition times between the productions may be relatively long and that make the grade transitions costly in comparison with the total amount 'on-spec' production. The optimization of complex operating processes generally begins with a detailed investigation of the process and its control system. It is important to know, how data-based information can support the optimization of product transition strategies. The optimization of product grade transition is a typical example for complex optimization in process industry (*McAuley and MacGregor*, 1992).

It is common to define an objective function, for example minimize the grade transition time, this way reducing off-specification products. The nonlinear behavior mainly appear during grade transitions, so handling these transitions with nonlinear models are complex and difficult problems to solve, so-called optimization strategies are time-consuming to define.

The control of polymerization reactors can be difficult and complex problem, due to the nonlinear dynamic behavior, the multiplicities of steady states, parametric sensitivity. One of the problems is the large amount of kinetic parameters, which are essential for creating a first principle model, but obtaining these parameters can be very time-consuming from the literature, laboratories, pilot-plants, and sometimes it is possible that the kinetic mechanism can not be available which can also make difficulties while making the first principle model. So it is useful to find those methods, where these pieces of information are not necessary, so model can be crated from input-output data, by identifying the model parameters, and it opens an easier way to develop an appropriate controller for the process from these data sets.

Unfortunately it is very difficult to find the right tuning parameters for the controllers in the whole operation range because of the nonlinearity of the process.Since the models provide the basis pieces of information for developing controllers the difference of a data-driven linear model and a more accurate first principle model can be significant.

Since the process trajectory within a processing stage depends on the process trajectory of the preceding stage, the rigorous approach is to treat the production optimization problem as a whole, including phases of transition as well as phases of production. This can be considered as a large-size real-time optimization (RTO) or dynamic real-time optimization (DRTO) problem (*BenAmor et al*., 2004), in which optimal set points or trajectories are calculated in order to minimize economic objectives subject to constraints. Several algorithms have been published to effectively solve this production optimization problem using dynamic optimization. These advanced algorithms can be formulated as a so-called multistage dynamic optimization problem, where the production time is split up into several processing stages. Most of these tools require accurate model of the process, which is not always available.

Treating this kind of optimization problems is the main target for us, and this paper would be an introduction to the optimization methods. In the industry the influence of model predictive control is increasing (*Camacho et al*., 1995), they are very successful in wide range of industrial applications. In most of the industrial applications the model predictive controllers are applied in the advanced control level as the part of the advanced process control (APC) systems. One of the main goal of this study is to explore the advantages of applying the model predictive controllers in the local control level as introducing the control problem as a optimization problem, since it is considered as the basic level of the multi-level optimization of a chemical plant. Nowadays more and more algorithms are available for planning model predictive controllers. It can be useful to compare the wide-spread applied PID controllers, and the increasingly applied model predictive controllers. For this study we choose a PI controller to compare with a dynamic matrix controller, and we qualified the performance with ISE (integral Square of Error) criteria.

Paper is organized as follows: the description of the polymerization process, define the purposes, introduce the theoretical basis of the solution and present the results.

THE CASE STUDY INVESTIGATION OF A POLYMERIZATION PROCESS

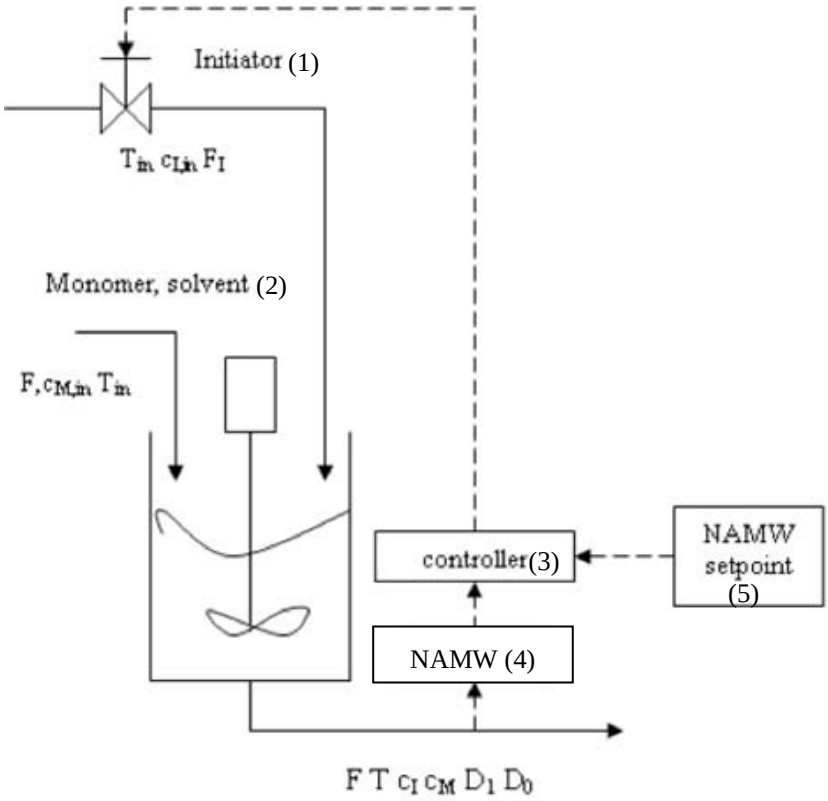
Process description

The reactor what have been studied is a SISO (single input-single output) process, a CSTR where a free radical polymerization reaction of methyl-metacrylate is considered using azobisisobutironitil (AIBN) as initiator, and toulene as solved (*Figure 1*). The aim

of the process is to producte different kinds of product grades. The number-average molecular weight is used for qualifying the product and process state, and it can be influenced by the inlet initiator flow rate. When this assumption is considered, and the effect of the temperature is neglected, the multi input-multi output model could be reduced to a SISO process. Because of the isothermal assumption a four-state model can be obtained. (*Maner and Doyle*, 1997)

Figure 1

The configuration of SISO polymerization process



1. ábra: A SISO polimerizációs folyamat sémája

Iniciátor(1), Monomer, oldószer(2), Szabályzó(3), NAMW(4), NAMW alapjel(4)

The monomer (methyl-metacrylate), the solvent (toulene), the initiator (azobis-isobutironitil) inlet is contionous to the reactor, an isotherm CSTR (Continously Stirred Tank Reactor), with a determined concentration. The inlet flow of the monomer is constant (F). The polymerization starts due to the amount of the initiator in the reactor. This influences the polymer chain length distribution (D_0-zero order moment of the chain length distribution) and the distribution of average molecular weight of the polymer (D_1–first order moment of the chain length distribution). From these pieces of

data the number average molecular weight (NAMW) can be calculated. This data is characteristic of every polymer product, so to control the pre-defined polymer quality the value of the NAWM is needed. When the value of the NAWM is different to pre-defined value the difference can be compensated by controlling the initiator inlet flow rate.

$$\frac{dC_m}{dt} = -(k_p + k_{fm})C_m P_0 + \frac{F(C_{m,in} - C_m)}{V} \tag{1}$$

$$\frac{dC_I}{dt} = -k_I C_I + \frac{F_I C_{I,in} - FC_I}{V} \tag{2}$$

$$\frac{dD_0}{dt} = (0.5k_{Tc} + k_{Td})P_0^{\,2} + k_{f_m} C_m P_0 - \frac{FD_0}{V} \tag{3}$$

$$\frac{dD_1}{dt} = M_m(k_p + k_{fm})P_0 C_m - \frac{FD_1}{V} \tag{4}$$

$$y = \frac{D_1}{D_0} \tag{5}$$

where:

$$P_0 = \left[\frac{2f * k_I C_I}{k_{Td} + k_{Tc}}\right]^{0.5}, \tag{6}$$

where:

C_m - concentration of the monomer in the reactor
$C_{m,in}$ - monomer concentarion in feed
C_I - initiator concentration in the reactor
$C_{I,in}$ - initiator concentration in feed
D0 - zero order moment of the chain length distribution
D_1 - first order moment of the chain length distribution
k_p, k_{fm}, k_I, k_{Tc}, k_{Td} - kinetic parameters (it can be seen in *Table 1*)

Table 1

Nominal values and kinetic parameters of the first principle model

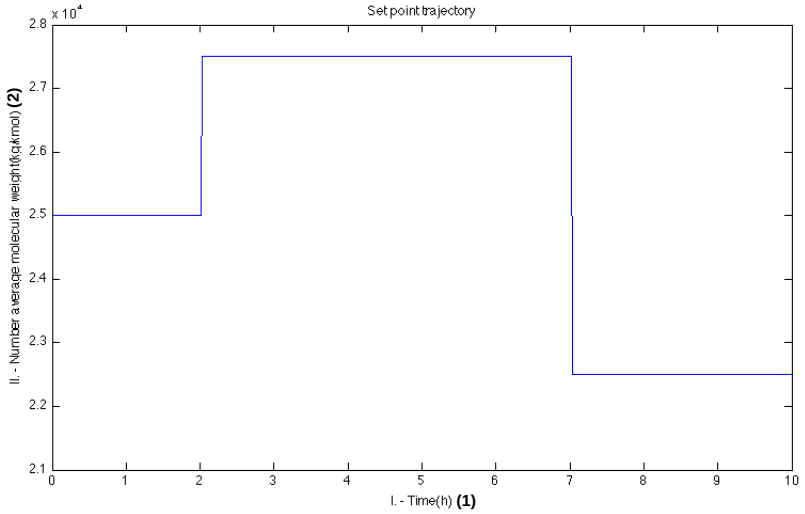
k_{Tc}=	1.3281×10^{10}	m3/(kmol*h)
k_{Td}=	1.0930×10^{11}	m3/(kmol*h)
k_I=	1.0224×10^{-1}	1/h
k_p=	2.4952×10^{6}	m3/(kmol*h)
k_{fm}=	2.4522×10^{3}	m3/(kmol*h)
f*=	0.58	
F=	1.0	m3/h
V=	0.1	m3
$C_{I,in}$=	8.0	kmol/m3
M_m=	100.12	kg/kmol
$C_{m,in}$=	6.0	kmol/m3

1. táblázat: A fehér doboz modell állandói és kinetikai paraméterei

Problem description
The task is producing three different kind of grades, called A, B, C (*Figure 2*)

Figure 2

The set point values of changing different productions



2. ábra: A termékváltás során alkalmazott alapjel trajektória

Idő (h)(1), Átlagos molekulatömeg (kg/kmol)(2)

To compare a MPC and a PI controller two grade transitions were chosen, one of them in the 2nd hour from A product ($NAWM_A$=25000 kg/kmol) to B product ($NAWM_B$=27500 kg/kmol). B has been produced in the next five hours, and in the 7th hour there is a grade transition from B to C product ($NAWM_C$=22500 kg/kmol).

The main goal is to minimize the amount of the off-grade product, so reduce the grade transition time as much as possible to show that there are reserved, untapped possibilities in the the process, and the model predictive controllers may have better performance than original PI controllers. The previously introduced set point data set is used to test the performance of the two different control algorithm, and these can be qualified using ISE (Integral Square of Error) criteria.

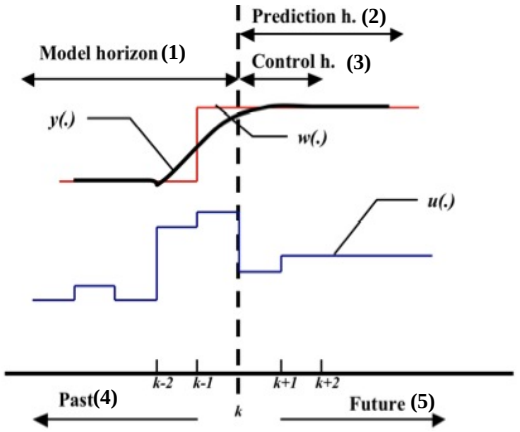
MPC BASED FORMULATION OF OPTIMAL GRADE TRANSITION

Model Predictive Controllers– theoretical basis
MPC is a model based control algorithm where the models are used to predict the behavior of dependent variables (i.e. outputs) of a dynamical system with respect to changes in the process independent variables (i.e. inputs). In chemical processes, independent variables are most often setpoints of regulatory controllers that govern valve movement (e.g. valve positioners with or without flow, temperature or pressure controller cascades), while dependent variables are most often constraints in the process

(e.g. product purity, equipment safe operating limits). The MPC uses the models and current plant measurements to calculate future moves in the independent variables that will result in operation that honors all independent and dependent variable constraints. The MPC then sends this set of independent variable moves to the corresponding regulatory controller setpoints to be implemented in the process. With the help of the *Figure 3* the essence of the model predictive controlling is easily understandable.

Figure 3

The essence of model predicitve controllers



3. ábra: A modell prediktív szabályozás lényege/működése

Modellezési tartomány(1), Predikciós tartomány(2), Szabályozási tartomány(3), Múlt(4), Jövő(5)

In this picture the essence and the advantage of the model predictive controllers can be seen. It means that using the model it becomes possible to predict the effect of the actual control signal in the future (in the prediction horizon) or to realize the set points in the future, how the control signal should be variated. MPC has the ability to reckon with the effect of the realized control signal (model horizon). The aim of the MPC is to minimize the error between the set points (w.) and the measured values (y.). It can be formulized in an objective function. To reduce the computing demand of solving the objective function, it is only solved on the control horizon, and this reducing is also necessary because the result of the objective function is a control signal trajectory, but just the first element of the the trajectory is realized. To get a contionous control signal the objective function is needed to be solved in every discrete moment.

Formulating the aim of the method, an objective function is the result, which is:

$$\min_{\Delta u(k+j)} \sum_{j=H_{p1}}^{H_{p1}} (w(k+j) - y(k+j))^2 + \lambda \sum_{j=1}^{H_c} \Delta u^2 (k+j-1) \tag{7}$$

where *w(k+j)* means the set point value, *y(k+j)* means the predicted dependent value in the *(k+j)th* discrete time moment, *Δu* means the incremention of the control signal, λ is an weight parameter.

The black box model – Impulse response model

The identification of the dynamic part of a block-oriented model is a challenging task. In practice, the identification of the parameters of the IRM (Impulse Response Model) may be troublesome due to the large number of them (*Ricker*, 1988).

In this case the identification parameters can be obtained easily using φ variable which means:

$$\varphi(i) = y(i) - y(i-1) \tag{8}$$

where y(i) is the output of the process in the ith moment. With the help of φ the parameters of the discrete impulse response model (IRM) can be calculated easily:

$$g_i = \frac{\varphi(i)}{\sum_{i=1}^{N} \varphi(i)} \tag{9}$$

where Δt denotes the sampling time, i the ith discrete time-step, and N is the model horizon. This results in a more parsimonious IRM model description, where the variance of the identification problem is decreased by the decrease of the number of the parameters to be estimated.

The model based predictive controller

The convolution model can be easily applied in model predictive control scheme. The control algorithm is based on the natural division of the system response into *free* and *forced* response terms (*Abonyi et al.* 2000):

$$y_m(k+t) = y_{forced}(k+t) + y_{free}(k+t) \tag{10}$$

where the forced output, $y_{forced}(k+t)$, depends only on the future inputs,

$$y_{forced}(k+t) = K\sum_{i=1}^{t} s_i \Delta u(k+t-i) \tag{11}$$

where $\{s_i\}$ are the gain independent step response coefficients defined by $s_i = \sum_{j=1}^{i} g_j$; and $\Delta u(k+t-i)$ denotes the change on the control variable: $\Delta u(k+t-i) = u(k+t-i) - u(k+t-i-1)$.

As the previous equation suggests, the forced response is calculated by using a linear model, because the steady-state gain, K, is calculated at the kth time step, and is assumed to be constant during the prediction. In control engineering practice such one step linearization is commonly used for simplifying the highly computational-demanding optimisation task. The proposed method differs from these approaches in the calculation of the *free response* of the system that represents the effect of the previous control signals that can interpreted as the future response of the process assuming that the process input is constant during the prediction horizon, H_p. Hence, convolution model is used to generate this *free response*, $y_{free}(k+i) = Q_i + y_s$, where the Q_i coefficients are (*Marchietti and Mellchamp*, 1983):

$$Q_i = \sum_{t=1}^{i}\sum_{j=t+1}^{N} g_j \Delta u(k+t-j), \qquad i = 1,2,..,H_p. \tag{12}$$

The future incremental control actions, $w = \left[w(k+1),\ldots,w(k+H_p)\right]^T$, are obtained by minimising the following cost function:

$$\min_{\Delta \mathbf{u}} = \left(w - \left(K\mathbf{S}\Delta\mathbf{u} + \mathbf{y}_{free}\right)\right)^2 + \lambda\Delta\mathbf{u}^2 \tag{13}$$

where w is the set point vector $w = \left[w(k+1),\ldots,w(k+H_p)\right]^T$ denotes the future set-point values, $\mathbf{y}_{free} = \left[y_{free}(k+1),\ldots,y_{free}(k+H_p)\right]^T$ the predicted free-response, and **S** is the gain independent dynamic matrix:

$$\mathbf{S} = \begin{bmatrix} s_1 & 0 & 0 & \cdots & 0 \\ s_2 & s_1 & 0 & & 0 \\ s_3 & s_2 & s_1 & \ddots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ s_{H_c} & s_{H_c-1} & s_{H_c-2} & & s_1 \\ \vdots & \vdots & \vdots & & \vdots \\ s_{H_p} & s_{H_p-1} & s_{H_p-2} & \cdots & s_{H_p-H_c+1} \end{bmatrix}_{H_p \times H_c} \tag{14}$$

The move suppression coefficient, λ, employs a punishment for the variation of the manipulated variable. For nonlinear processes this constant can be gain-scaled by expressing it as a product of a scaled move-suppression coefficient, γ, and the square of the process gain, $\lambda = \gamma \cdot K^2$ (*Shridhar, Cooper,* 1997).

If the process constraints are not taken into account, the previous minimisation problem can be solved effectively by least-squares method,

$$\Delta u = \frac{1}{K} \cdot (S^T \cdot S + \gamma \cdot I)^{-1} \cdot S^T \cdot e \tag{15}$$

where **e** is the vector of the estimated errors **e = r - $\mathbf{y}_{free}$**, and **I** is a unity matrix.

The controller has three parameters. These are the prediction horizon, H_p, the control horizon, H_c, and the gain independent move suppression coefficient, γ. The prediction horizon should roughly be equal to the 60% of the open loop settling time to ensure controller stability. When the process in nonlinear, the open-loop settling time is changing with the operating point. According to this effect, the prediction horizon can be adapted during the operation. A simpler solution is setting the prediction horizon equal to the 60% of maximum of the settling time. In the application study of this paper we consider the linear model of the process, and we consider the move-suppression coefficient, $\gamma = 4.7058*10^9$. The value of the move suppression coefficient was obtained with a parameter sensitivity.

MODEL PREDICTIVE CONTROL OF A SISO POLYMERIZATION PROCESS

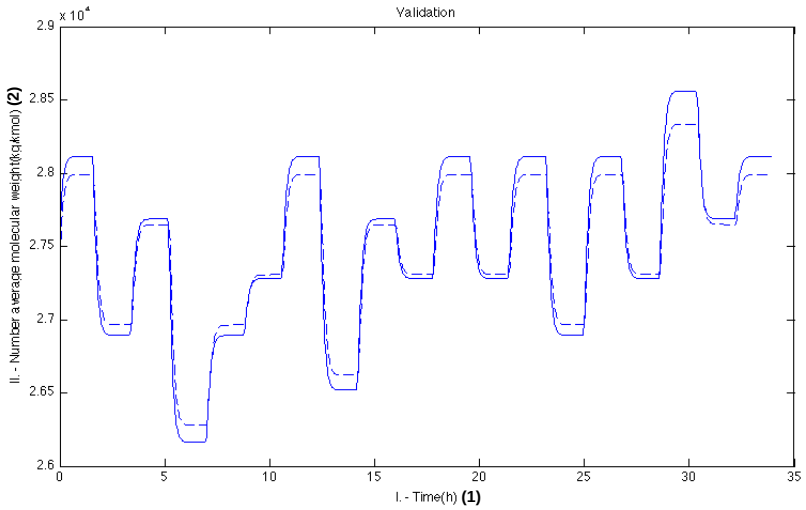
Model Identification

For this study we generated input-output data with the white-box model, using sample time Ts = 0.03h. We identificated our black-box model by these data-sets. Our black box model is the impulse response model and the step response model, the integral of IRM.

Because of the nonlinearity of the white box model, we have chosen a steady state point and we identified our black box model around this point (*Figure 4*). After identification the model was validated, because of the control of its' reliability.

Figure 4

Validation of the black box model



4. ábra: Az identifikált konvolúciós modell validálása

Idő (h)(1), Átlagos molekulatömeg (kg/kmol)(2)

To use the black box model for desing a model predictive control the identificated black box model is needed to be validated. In this figure the validation can be seen. The blue line means the response of the black box model and the red line means the response of the first principle model for the same input signal. The two responses show some difference because of the nonlinearity of the first principle model, which is obviously has a different response than the linear black box. As the figure shows it can be stated that the linear model is appropriate for approximating the response of the non-linear linear model, so this linear model can be applied for design a MPC.

RESULTS

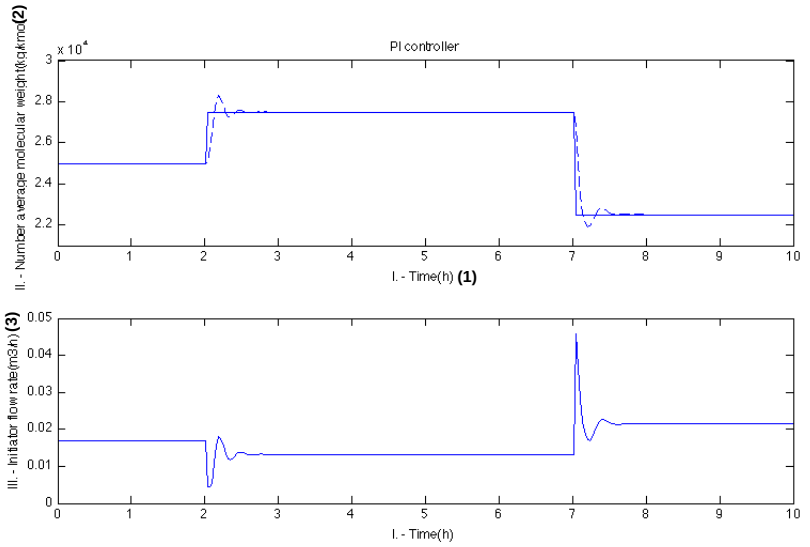
The tuning parameters were selected to obtain satisfactory set-point tracking. In this case setpoint changes mean grade change (determined by the certain values of the NAMW). We have studied a PI controller and a model predictive contoller, DMC. The control signal is between the range u = [0.0046, 0.05] m^3/h in both cases. The PI controller was implemented to the white box model and, the tuning parameters of it has been obtained the following way: a first order plus dead time model was identificated and applying the parameters of this model the tuning parameters of PI controller could be obtained with ITAE method. The controller tuned this with this method can provide a good result during the grade transitions, as it can be seen in the *Figure 5.*

The task is to realize the chosen grade-transitions ('A' product to 'B' product in the 2^{nd} hour and 'B' product to 'C' product in the 7^{th} hour) with a wide-spread applied PI controller. The products can be charaterized with the number average molecular weight (NAMW (kg/kmol)). To control the NAMW the initiator flow rate (the control signal) is varied. The

maximum value of the control signal is 0.05 m3/h, the minimum value is 0.0046 m3/h. The grade transitions last approximately an hour, and to qualify these transitions the ISE (Integral Square of Error) can be calculated. The result is ISE = $3.8418*10^7$. ISE becomes possible to compare the PI controller to the MPC.

Figure 5

Simulation with PI controller



5. ábra: A PI szabályozóval elvégzett szimuláció eredménye

Idő (h)(1), Átlagos molekulatömeg (kg/kmol)(2), Iniciátor térfogatáram (m^3/h)(3)

The PI parameters: K = $-6.78*10^{-6}$ TI = 0.225 h, which can ensure a good kind of controlling. So the new set point (from 25000 kg/kmol to 27500 kg/kmol) is obtained in 1 hour, with a overshoot with approximately ¼ decay ratio, and an other set point change in 7^{th} hour, and the new set point is obtained in an hours.(green line is the set point signal, blue is the measured signal(NAWM) in both cases). So the length of the grade transition time can be seen a little bit long, so finding a method is neccessary to reduce the grade transition time, or finding a control algorithm which can provide producing less off-grade product.

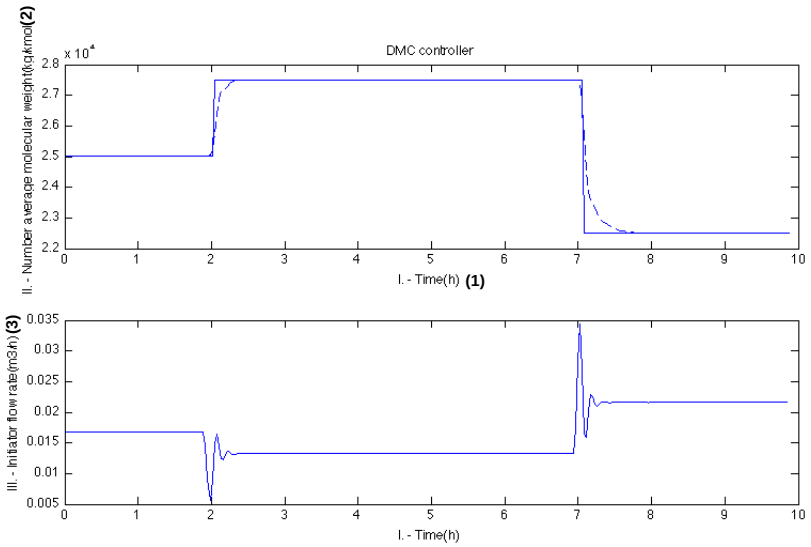
The model predictive controller provides very different kind of controlling due to the lack of the overshoot. The set point is the same like in the case of PI controller, because of the comperableness.

The tuning parameters of DMC, is the lenght of the prediction horizon, control horizon, and the value of the λ parameter, and it is also important to define the lenght of model horizon. The model horizon is N = 30, which was obtained by using the impulse response model (IRM) of process. The prediction horizon is selected to be p = 5 because increascing the prediction horizon the quality of controlling is getting worse. The control

horizon is selected to be $c = 4$, because when the length of the control horizon converges the value of the prediction horizon the controller becomes more aggressive (*Figure 6*).

Figure 6

Simulation with DMC controller.



6. ábra: A DMC szabályozóval végzett szimuláció eredménye

Idő (h)(1), Átlagos molekulatömeg (kg/kmol)(2), Iniciátor térfogatáram (m^3/h)(3)

The task is the same as the simulation with the PI controller. The operating conditions are also the same. Compare this figure to the previous figure it can be stated that the DMC is faster in the first grade transtion (’A’ to ’B’), approximately 0.5 hour. The second grade transition (’B’ to ’C’) takes the same time (1 hour). The advantage of the DMC can be observed when the value of the ISE has been calculated (ISE = $2.5773*10^7$).

The behavior of DMC controller is definitely different to the PI controller, but the DMC can be a little bit faster than the PI controller and has no oveshoot.

Examining only the figures the advantage of any controller is very difficult to state. The error of the PI controller (calculated by ISE method) was $3.8418*10^7$, but the DMC controller can afford $2.5773*10^7$ error. So the advantage of DMC can be stated. Tuning these two controllers more agressively would result additional ostillations, and lenghten the time it takes for them to keep the number average of molecular weight in in accurate value, so a compromise is needed to be made in tuning the controllers for servo-mode.

CONCLUSION

In the chemical industry the importance of the polymerization processes is increasing. To develop these processes the length of the grade transitions are needed to reduce, because this way it becomes possible to avoid to produce off-grade products. To reach

this demand a MPC algorithm was used to handle the grade transitions. In this work a PI and a MPC controller were compared each other. First we use the first-principle model of a polymerization process, and using this the black box model was identified. Using the impulse response and the step response model of the reactor, the DMC could be build for this reactor. It is seen that the performance of the model predictive controller is better, than the performance of PI algorithm. It is also proved by the ISE criteria. The applicability of applying the model predicitve controllers in the local control level is confirmed also by the ISE criteria and the visual comparison. The actuality of handling the control problem as an optimization problem is very high. Generally, it is very important to find the best fitting contoller algorithm to realize the objecive function. In a lot of cases the advantage of MPC algorithms fits better to these objective function, but they have a huge disadvantage: in most cases it is necessary to use linear model approaches which are very sensitive for the identified parameters, and in nonlinear systems these parameters can change different kind of methods are available. The non-linear model predictive controllers can handle this problem, or adaptive algorithms are able to solve them. Regarding to the the increasing spread of MPC controllers, because of the rising industrial demand, it would be useful to develop the nonliner model predictive controllers, because of the hope of better performance of the whole operating range.

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REFERENCES

Abonyi J., Bódizs Á., L, Nagy L., Szeifert F.(2000): Hibrid fuzzy convolution model and its' application in predective control. Chemical engineering research & design, 78.^{o}4. 597-604 p. (26 ref.)

BenAmor S., Doyle F.J., McFarlane R. (2004): Polymer grade transition control using advanced real-time optimization software. In: Journal of Process Control 14. 349-364 p.

Camacho E.F., Bordons C. (1995): Model Predictive Control in the Process Industry. Springer : London

Maner B.R., Doyle F.J. (1997) Polymerization reactor control using autoregressive volterra-based MPC. In: AIChe Journal 43. 1763-1784. p.

Marchetty J.L., Mellchamp D.A., Seborg D.E. (1983): Predictive Control Based on Discrete Convolution Models. In: Ind. Eng. Chem. Res. Dev. 22. 488-495. p.

McAuley K.B., MacGregor J.F. (1991): On-line Inference of Polymer Properties in an Industrial Polyethylene Reactor. In: AIChe Journal 37. 825-835 p.

Ricker N.L. (1988): The Use of Biased Least – Squares Estimators for Parameters in Discrete – Time Pulse Response Model. In: Ind. Eng. Chem. Res. 27. 343-350. p.

Shridhar R., Cooper D.J. (1997): A Tuning Strategy for Unconstrained SISO Model Predictive Control, In: Ing. Eng. Chem. Res. 36. 729-746 p.

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