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EXPERIMENTAL APPLICATION OF THE ITERATIVE LEARNING CONTROL TO THE TEMPERATURE CONTROL OF BATCH REACTOR

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Abstract: A learning control solution to the problem of finding a finite-time optimal control history that minimizes a quadratic cost is presented. Learning is achieved without requiring a detailed knowledge of the system, which may be affected by unknown but repetitive disturbances. The objective of this work is considered as a validation of the results obtained in (Mezghani, *et al.,* 2001). It focuses on the temperature control of a semi-batch chemical reactor used for fine chemicals production. Such reactor is equipped with a heating/cooling system composed of different thermal fluids. With less modelling investigation, a feedback-feedforward control structure is proposed for ensuring the tracking performance of the desired temperature profile. Such strategy is derived from the family of the Iterative Learning Control named Batch Model Predictive Control (*BMPC*). The synthesis of the considered strategy is studied and improvements of the algorithm features are proposed. A robust supervisory control procedure is employed to choose the right fluid and to reduce the superfluous fluid changeovers. Experimental results are presented to illustrate the practical appeal and effectiveness of the proposed scheme.

Keywords: Model based control; Iterative learning control; Batch chemical reactors; Temperature control; Pilot plant; Experimental validation

1. INTRODUCTION

Batch manufacturing of pharmaceutical products has been a fast growing part of the chemical processing industry where the same batch plant must be able to rapidly reply to different processing operations under different operating conditions and to the manufacturing of a variety of products. Such multipurpose, multi-product definition of a batch plant creates certain special challenges and requires the development of special techniques for control, analysis and monitoring of batch operation, which are quite distinct from their counterparts employed in continuous processes (Jupa, and Hamer, 1986; Berber, 1995).

Current research approaches to monitoring batch processes have focused on the uses of fundamental mathematical models, detailed knowledge-based models (Frank, 1990) or the process repetitiveness. The first takes advantage of a mechanistic model to describe the process, where the monitoring procedure is based on state estimation methods. The second relies on the knowledge of operators and engineers about the process to formulate control algorithms. The third takes advantage from the field of Iterative Learning Control (*ILC*), where learning can be intuitively considered as a bridge between knowledge and experience.

Since, batch processing are essentially dynamic operations over a wide range of operating conditions, consequently, conventional control and diagnosis techniques for continuous processes which rely on the stationarity of a nominal steady state are not applicable.

The concept of (*ILC*) was originally introduced in 1984 by Arimoto, *et al.,* (1984) who presented an algorithm that generates the new trial control input by adding a "*correction*" term to the control input of the previous trial. This is the key feature that distinguishes the *ILC* from the conventional feedback control (Bien, and Xu, 1998 , Moore, 1998). In the field of batch process control, the diversity of studies is only focusing on the adopted learning mechanism. In spite of the wealthy available simulation results (Mezghani, *et al.*, 2001, Katoh, *et al.*, 1989, Geng, *et al.*, 1989, Chen, *et al.*, 1994, Lee, *et al.*, 1996, Chen, *et al.*, 1997), few experimental results are available in the field of batch process control (chemical reactor) (Chin, *et al.*, 1997). In this work, we are mainly focusing with the temperature control of a semi-batch chemical reactor by using the *ILC* control approach, which is illustrated by some experimental trials.

In order to improve the tracking control of batch processes (namely by keeping with the on-line disturbance removal and constraints handling) an elaborated learning control algorithm was developed by (Lee, *et al.*, 1999). Such algorithm combines the predictive control enhancements with the iterative learning control ones under the name of Batch Model Predictive Control (*BMPC*). Under this advanced learning control technique, the *BMPC* approach will be investigated in our studies.

The remainder of this paper will be presented as follows: section 2 provides a brief description of the semi-batch chemical reactor, its environment and the associated thermal control strategy. Based on the derived input/output model, the model of the whole repetitive operation is presented. In the next section, the corresponding predictor will be defined, the latter one incorporates two indexes: the batch number (k) and the time evolution (t) during the batch. In section 4, we recall the control strategy. Practical issues are considered in the actual implementation such as reinitialization of the output error sequence, off-line filtering and robust supervisory thermal control. Extensive experimental results are included to illustrate the effectiveness and the practical appeal of the *BMPC* scheme faced with: repetitive disturbances and model mismatch. Finally, conclusions are drawn.

2. PROCESS DESCRIPTION AND MODELLING

2.1. Process description

The experimental runs were carried out on a pilot reactor that is considered as a test-bed for new control strategies, which can be implemented on industrial sites. This reactor is a 16 litres, glass-lined reactor (with a maximum operating volume of 12 litres). Three utility fluids are available at given temperatures: a mixture of monopropylene glycol/water (50%/50% weight, at a temperature of -10°*C*), cold water (at a temperature of 15°*C*) and steam (at a pressure of 6 bars). A so-called "intermediate fluid" is obtained by direct mixing of cold water and steam, where the maximum reached temperature is about 70°*C*. Compressed air is available for the purge of the jacket when a fluid changeover is required. A schematic diagram of the pilot-plant glass-lined jacketed reactor and its heating/cooling system is depicted on figure (1). The SCADA and the presented BMPC algorithm software have been operated under *LABWINDOWS/CVI* environment implemented on a Personal Computer (*P200*).

The pilot reactor is surrounded by a pipe-net for each thermal fluid delivery, which is equipped by instruments for data acquisition and control. These instruments include sensors of temperature and pressure, flowmeters and electro-pneumatic valves. Six temperature sensors are used to measure the following Temperatures: jacket inlet temperature (T_e), jacket outlet temperature (T_s), mixer outlet temperature (T_m), cold water inlet temperature (T_{ef}), steam temperature (T_v) and reactor temperature (T_r). Four flowmeters are used to measure the flow rate of these different fluids: cold water (D_1), intermediate fluid (D_2), glycol water (D_3) and steam (D_4). Four proportional electro-pneumatic valves (V_A , V_B , V_C and V_D) are implemented for the control of the utility fluid flow rates. Twelve on/off valves (V_1, …, V_{12}), are used for ensuring the fluids circulation. The pilot-plant is also equipped with a recycling pump of the intermediate fluid.

2.2. Thermal control strategy

The heating/cooling system is a hybrid configuration, which integrates the advantages of both the mono-fluid and multi-fluid systems (Cabassud, *et al.*, 1995). This hybrid system allows to use either water as intermediate thermal fluid (which is industrially much cheaper than other thermal fluid) either glycol water or steam when, respectively, a colder or hotter fluid is needed. The thermal control strategy is based on the use of the thermal flux exchanged between the utility fluid and the mixture as the manipulated variable. The control strategy is composed of a model based on the iterative linear learning controller (*BMPC*) cascaded with two blocks (figure (2)). The first one is a supervisory control block enabling the choice of the adequate thermal fluid based on thermal flux limits analysis (intermediate fluid, glycol water or steam). The maximal and minimal thermal capacities of each fluid are computed to allow this choice. In the case of a conflict, the priority is given to the current fluid. The second block is a non-linear block ensuring computations of the fluid flow rate (based on the corresponding thermal fluid model) and of the resulted opening degree of the valves to be applied. The thermal flux computed by the *BMPC* controller is compared to the limit capacities of the current fluid. Thermal limits capacities computations are not detailed in this paper, the interested reader should consult (Louleh, *et al.*, 1996).

2.3. Modelling

A dynamic process can be represented generally by a set of differential equations (in the time domain) or a transfer function (in the frequency domain). Since, the considered system to be studied, belongs to the class of repetitive systems, where a repeated operation task is defined over a finite time interval, the construction of a dynamic model linking all the process input/output during the whole operation is rather credible to achieve better performance of the repeated operation. It can be considered as a two-dimension model, which is a function of the time evolution of the process behaviour during the considered operation (index t) and the batch number (index k). This partial knowledge of the process behaviour is essentially based on energy balance equations on the reacting mixture and on the reactor jacket wall (Mezghani, *et al.*, 2000). Then, the model of the whole operation model can be derived by integrating the energy balance equations.

By considering the following operation sequences $\boldsymbol{y_k}$, $\boldsymbol{u_k}$ and $\boldsymbol{p^r}$ (see figure (3)), the sequence $\boldsymbol{y_k}$ can be rewritten in a vector form, as a function of the $\boldsymbol{u_k}$ and $\boldsymbol{p^r}$ sequences.

$$\boldsymbol{y_k} = \boldsymbol{G u_k} + \boldsymbol{p^r} \qquad (1)$$

With:

$\boldsymbol{G}$ matrix is a lower triangular matrix, where components are the *Markov* parameters of the nominal model given by the discretisized energy balance equations, for more details see (Mezghani, et al., 2000).

$$\boldsymbol{y_k^T} = [y_k(1), y_k(2), \cdots, y_k(N)]$$

$$\boldsymbol{u_k^T} = [u_k(0), u_k(1), \cdots, u_k(N-1)]$$

$$\boldsymbol{p^{r\,T}} = [p^r(1), p^r(2), \cdots, p^r(N)]$$

with (see figure (3)):

N : batch time (in number of sampling times),

$\boldsymbol{y_k}$: output sequence of the k^{th} batch,

$\boldsymbol{u_k}$: control sequence of the k^{th} batch,

$\boldsymbol{p^r}$: sequence of the non-repetitive disturbances (disturbances due to unmodelled dynamics and the free response sequence caused by initial conditions of the state vector (x_0)).

3. PREDICTOR SYNTHESIS

The presented strategy allows to keep on one hand, with the Model Predictive Control (*MPC*) methodology (Richalet, *et al.*,1978), using a linear finite memory output predictor (based on the internal representation of the uncertain process to be controlled), and on the other hand, with the Iterative Learning Control (*ILC*) strategy based on the previous input/output information during the repetitive operation. The adopted strategy is based on combining the *MPC* features with the *ILC* features under the name of Batch Model Predictive Control (*BMPC*). The resulting strategy integrates both properties of feedback and feedforward actions respectively to the *MPC* and the *ILC* controllers.

While, the interest is to improve performance operations from one batch to the next one, the available formulation of the whole operation given by equation (1), does not exhibit a recurrent formulation that takes into consideration the batch number (k) and the time evolution (t) during the batch. Therefore, in order to embed both control actions: feedback (current batch measurements) and feedforward (previous batch measurements), it is recommended to dispose of a model incorporating two indexes (k, t).

The computations of the control values in the *BMPC* require predictions of the output error sequence $\boldsymbol{e_k}(t/t)$ over the horizon (m). The one step predictor of the output error sequence is given by:

$$\boldsymbol{e_k}(t/t-1) = \boldsymbol{e_k}(t-1/t-1) - G_t \Delta u_k(t-1) \qquad (2)$$

$$\boldsymbol{e_k}(t/t) = \boldsymbol{e_k}(t/t-1) + \boldsymbol{K_k}(t)(e_k^m(t) - e_k(t/t-1))$$

Where

- $\boldsymbol{K_k}(t)$ represents the dynamic matrix of the Kalman filter which is determined by minimizing the covariance error of the estimated error sequence.

- $e_k^m(t/t)$ and $e_k(t/t-1)$ represent respectively the measured and the estimated tracking error during the k^{th} batch at the instant t (Chin, et al., 1997) :

$$e_k(t/t-1) = \boldsymbol{H}(t)\boldsymbol{e_k}(t/t-1) \qquad (3)$$

With :

$$\boldsymbol{H}(t) = [0_{[1\times t-1]}, 1, 0_{[1\times N-t]}] \ \text{ with } 1 \le t \le N$$

Then, the m step ahead predictor $\boldsymbol{e_k}(t+m/t)$ can be obtained as follows:

$$\boldsymbol{e_k}(t+m/t) = \boldsymbol{e_k}(t/t) - \boldsymbol{G}^{t+m} \Delta \boldsymbol{u_k^{t+m}} \qquad (4)$$

where :

$$\boldsymbol{G}^{t+m} = [G_t, \ldots, G_{t+m-1}]$$

$$\Delta \boldsymbol{u_k^{t+m}} = [\Delta u_k(t), \ldots, \Delta u_k(t+m-1)]^T$$

4. CONTROLLER SYNTHESIS

According to the conventional predictive control strategy (Garcia, *et al.*,1989), the performance objective consists in minimizing a quadratic criterion ensuring a compromise between the tracking quality and the dissipated energy. Similarly, the *BMPC* control law is designed with the aim to minimize the following criterion (Lee, *et al.*, 1999) :

$$\min_{\boldsymbol{u_k^{t+m}}} \frac{1}{2}\left\{\boldsymbol{e_k}(t+m/t)^T \boldsymbol{Q}\boldsymbol{e_k}(t+m/t) + \Delta\boldsymbol{u_k^{t+m}}^T \boldsymbol{R}\Delta\boldsymbol{u_k^{t+m}}\right\} \qquad (5)$$

where m is the control horizon. Δ is the integral action according to the batch index. Note that no controller outputs u_k^{t+m} but only their increments Δu_k^{t+m} are penalized. The reason is to ensure that the mean of the tracking error ($\boldsymbol{y_k} - \boldsymbol{y_{k-1}}$) will be near zero when $k \to \infty$ (steady state of the successive carried out batches). $\boldsymbol{Q}$ and $\boldsymbol{R}$ are two definite, positive and symmetric matrices. It is to be noted that this performance criterion is composed of two terms: the first one is the sum of the future predicted output square errors where the predictions are based on current measurement (at instant t), previous batch measurements from ($t \to t+m$), control value increments sequence computed at each step (Δu_k^{t+m}), noise covariance matrices and the truncated part of the matrix $\boldsymbol{G}$ (G^{t+m}). The second term represents the future control increments square over the prediction horizon m penalised by the matrix R. According to the established m-step ahead predictor (4), the criterion (5) can be expressed by an algebraic matrix form and the computation of the future control increments sequence (Δu_k^{t+m}) minimising the criterion is immediate. Hence, from the least square formula, the expression of the optimal sequence (Δu_k^{t+m}) is readily obtained:

$$\boldsymbol{u}_{\boldsymbol{k}}^{t+m} = (\boldsymbol{G}^{t+m^T} \boldsymbol{Q}\boldsymbol{G}^{t+m} + \boldsymbol{R})^{-1} \boldsymbol{G}^{t+m^T} \boldsymbol{e}_{\boldsymbol{k}}(t/t) \quad (6)$$

and the first component of the vector Δu_k^{t+m} is considered as the instantaneous correction term to the control value computed at the previous batch. The control value is given by:

$$u_k(t) = u_{k-1}(t) + \Delta u_k(t) \quad (7)$$

Besides, the necessary Kalman filtering, which is needed to improve such control strategy in terms of control performances, it is necessary to get a smooth control action (to prevent from equipment damage) and a fast convergence rate. Based on the learning concept, the control variance is continuously increasing. In order to be able to enhance the behaviour of such batch process some supervisory control tasks has to be considered: (1) off-line filtering of the previous computed control sequence, (2) strategy for the right selection of the thermal fluid by taking advantage of the knowledge of the future control values computed at each sampling time, for further details see (Mezghani, *et al.*, 2001).

5. EXPERIMENTAL STUDIES

In this study, experiments involve chemical reaction, which have been simulated using heat source for exothermic reactions. For safety and experimental cost saving, the pilot plant reactor has been fitted with heating resistances. This device allows the "simulation" of the generation of heat during an exothermic chemical reaction as described in (Kershenbaum and Kittisupakorn, 1994). The heat generation rate is computed on-line according to the kinetic model of the chemical reaction concerned. This value is then applied to the process by means of the heating resistance. The time evolution of the heat generation rate is presented on figure (4). The *BMPC* computations of the first batch are initialised by the input/output data obtained through the application of the generalized predictive controller (*GPC*). This is done according to experimental studies investigated in (Mezghani, *et al.*,2000). The choice of *GPC* controller is not a restriction and any conventional controller can be used to provide the *BMPC* initialisation. More precisely such studied strategy can be resumed in two steps design: (1) at the first trial: the use of a conventional feedback controller (i.g. *GPC*), (2) at next trials: the use of an Iterative Learning Controller (*BMPC*).

To illustrate some of the *BMPC* features, two successive experimental run sets have been carried out (T_{pal} =45°C and 60°C). A classical four steps profile tracking is considered: (1) a preheating step of the initial mixture (The reactor has been charged with 10 litres of water) from ambient temperature to T_{pal} during 900 *s*, (2) a maintaining temperature step (T_{pal}), from 900 *s* to 2700 *s*, with the "simulation" of the reaction by the two heating resistances, from 1200*s* to 2200 *s*, (3) a cooling step of the mixture from 60°*C* to 35°*C* during 800 *s*, to prevent the formation of secondary products, (4) a maintaining step at 35°*C* during 100 *s*. The outline of such experimental studies can be organized as follows: (1) firstly, to illustrate the convergence of the algorithm, in the presence of a repetitive perturbation (heat released by an exothermic chemical reaction), (2) secondly, to evaluate superfluous fluid changeovers via a convenient handling of the different heating/cooling fluids.

For the presented examples, m=10, $\boldsymbol{Q}=\boldsymbol{I}$, $\boldsymbol{R}=10*\mathbf{I}$, $\boldsymbol{R_w} = \boldsymbol{R_v} = \boldsymbol{J}$, where $\boldsymbol{I}$ is the identity matrix and $\boldsymbol{J}$, the dynamic matrix of low frequency perturbations. More details on the choice of these synthesis parameters ($\boldsymbol{G}$, *m*, *Q*, *R*, $\boldsymbol{R_w}$, $\boldsymbol{R_v}$, $\boldsymbol{J}$) can be found in (Mezghani, *et al.*, 2001).

Experimental set $n^o 1$: T_{pal} = 45°C

Figure (5-a) depicts the reactor temperature during the successive batches. First of all, with the BMPC it is possible to progressively decrease the disturbance effect due to the heat generation rate (not included in the process model) in a few successive experiment runs (four successive runs as shown on figure 5-a). Secondly, there is not a degradation in the performances during the preheating and the cooling steps as tracking performances are notably similar to those obtained by the *GPC* controller. Figure (5-b) displays the thermal flux minimal and maximal capacities of each fluid, the thermal flux computed by the *GPC* controller (initial data required for the *BMPC* computations) and the thermal flux computed by the *BMPC* controller at the 4^{th} batch. In this experiment, the intermediate fluid was used during the preheating and the cooling and a changeover to glycol water was needed during the maintaining step to cancel out the heat generation. As it can be seen in figure (5-b), one of the main advantages of the *BMPC* is the powerful capacity of anticipation in the changeovers of fluid. The first changeover occurs at 1200s merely 100 seconds before the one performed in the initial experiment (with the *GPC*).

Experimental set $n^o 2$: T_{pal} =60°C

In order to illustrate the robust handling in such thermal control system equipped with several fluids, the performance of the *BMPC* controller are tested for the same four step temperature profile but with a maintaining temperature of 60°C. Figure (6-a) shows the successive process output behaviour. Figure (6-b) depicts the thermal maximal and minimal capacities of each fluid and the thermal fluxes computed by the *GPC* and the *BMPC* (4^{th} run) controllers. Since faster heating and cooling phases are required, the successive use of the intermediate fluid and steam during the preheating step and of glycol water during the maintaining and the cooling steps is needed. Notable improvements can be observed not only in the cancellation of the disturbance but also in the tracking performance at the end of the cooling step. Similarly to the previous experimental set, it can be noted that an earlier switch to the glycol water is performed with the BMPC that confirms the anticipation capacity of such a strategy. As previous, the disturbance is nearly cancelled after a few number of experimental runs (four successive runs). It is to be noted that, during the preheating step (figure 6-b) and for the four batches, the switch from the intermediate fluid to the steam is always accompanied by a temperature overshoot, which cannot be improved by the *BMPC* controller. This is essentially due to the reactor jacket wall inertia and its assumed static thermal model presented by (Mezghani, *et al.*, 2000 ; Louleh, *et al.*, 1996).

6. CONCLUSION

The experimental results have illustrated the improvement of the achieved performance applied to a semi-batch chemical reactor equipped with a thermal system composed of several fluids by using an appropriate Iterative Learning Controller. The robust strategy dedicated to the class of repetitive operations has been evaluated for different maintaining temperature profiles. Thus, various scenarios have been tested: the impact of noise affecting the measured data and of uncertain physical parameters used to derive the dynamic matrix $\boldsymbol{G}$ (the uncertain real process). In order to ensure a compromise between robust performance and learning convergence rate, an appropriate filtering has been investigated. In spite such successful results, interesting questions and critical points for the actual implementation should be mentioned. Notably, the algorithm should be extended to non-linear plants and using more complicated performance criteria should perform improvements of the rate of convergence.

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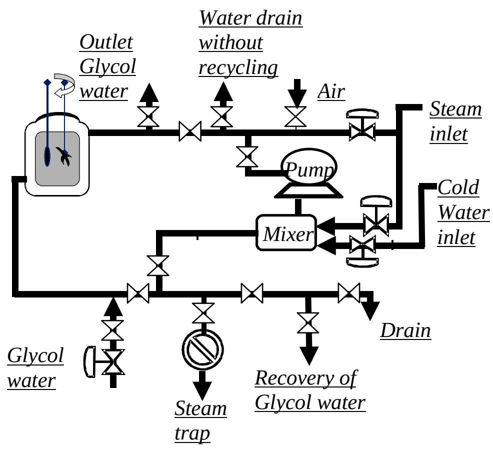


Fig. 1._Scheme of the pilot plant reactor.

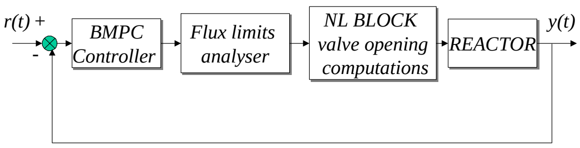


Fig. 2. Closed loop scheme of the reactor and its environment.

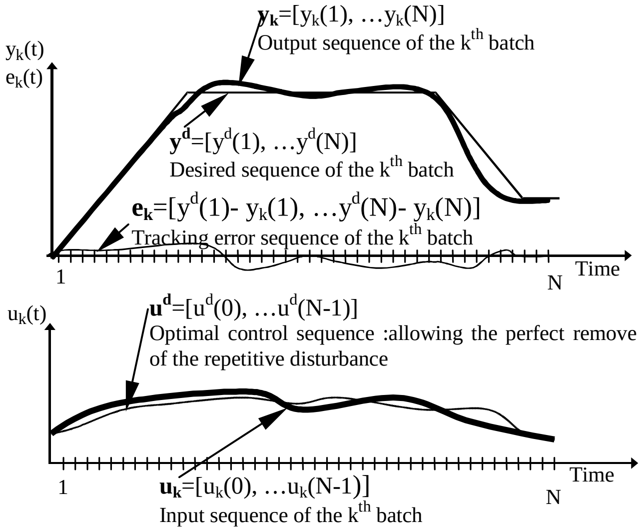


Fig. 3. Descriptive scheme of the repetitive disturbed operation.

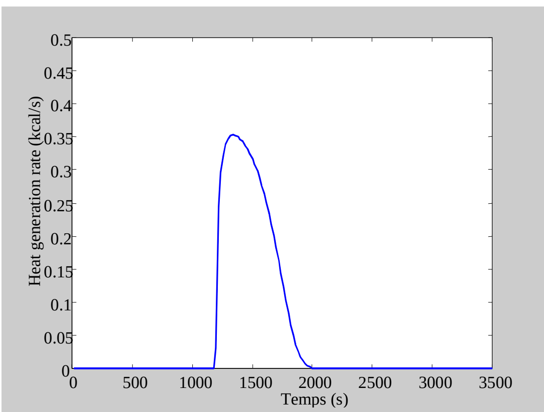
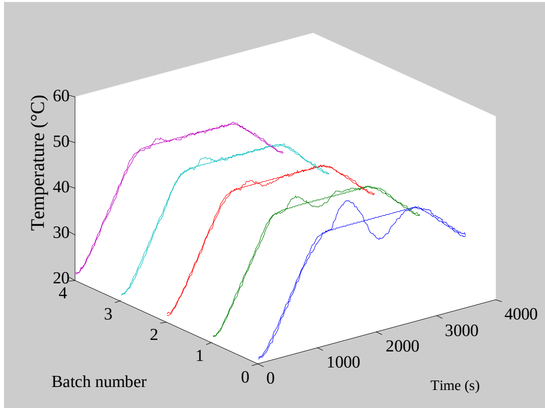
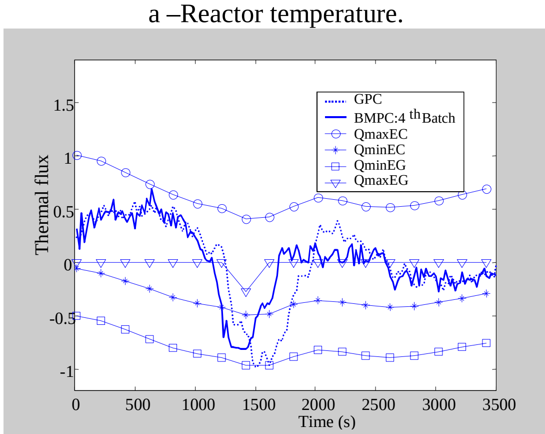


Fig. 4. Heat generation rate profile applied to two immersed resistances.

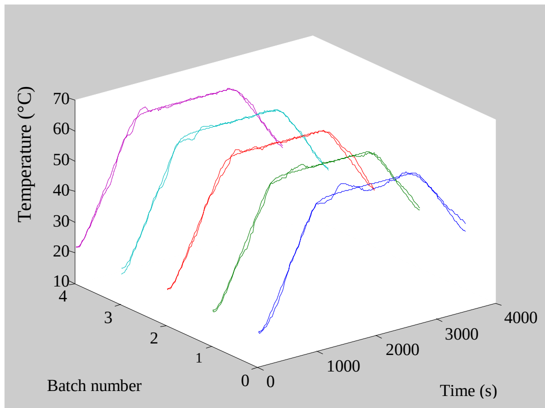


a –Reactor temperature.

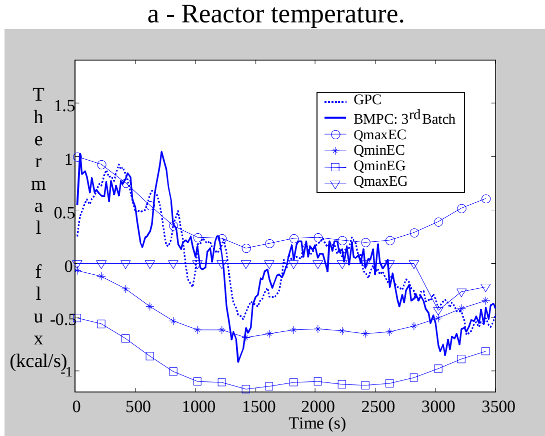


b - Controller output and thermal flux of each fluid.

Fig. 5. Experimental results of set *n°1*.



a - Reactor temperature.



b - Controller output and maximal/minimal capacities of each fluid

Fig. 6. Experimental results of set *n°2*.