Centralized vs decentralized adaptive generalized predictive control of a biodiesel reactor

Yong Kuen Ho, Farouq S. Mjalli1,2* and Hak Koon Yeoh1

1Chemical Engineering Department, Faculty of Engineering, University of Malaya, 50603, Kuala Lumpur, Malaysia
2Department of Petroleum & Chemical Engineering, Sultan Qaboos University, 123, Muscat, Oman

Received 22 September 2011; Revised 29 February 2012; Accepted 19 March 2012

ABSTRACT: A second look at biodiesel reactor control using Recursive Least Squares (RLS)-based adaptive Generalized Predictive Control (GPC) strategy revealed the possibility of a simpler alternative to the previously published centralized RLS-based GPC controller (CRLS-GPC). New results show that the simpler decentralized RLS-based GPC controller (DRLS-GPC) was on par with the more sophisticated centralized version in terms of servo and regulatory control, process interactions handling, and the resultant controller moves. Moreover, the simplified control scheme remained superior to the conventional Proportional–Integral controller. Such attributes make the DRLS-GPC an attractive compromise between complexity and performance. © 2012 Curtin University of Technology and John Wiley & Sons, Ltd.

KEYWORDS: biodiesel; transesterification; recursive least squares; generalized predictive control; adaptive predictive control

INTRODUCTION

Biodiesel reactors resemble the heart of biodiesel production facilities (cf. Mjalli et al.[1] for the process description and mathematical model of the reactor). A few nonconventional biodiesel production processes (e.g. microwave biodiesel reactor etc.) alongside with their process control aspect are available in the literature.[2–4] For batch biodiesel reactors, Benavides and Diwekar employed an optimal control strategy to address the control issue.[5] Where the control of continuous stirred-tank (CSTR) type of biodiesel reactors are concerned (which is also of direct interest to this current work), Sanposh et al.[6] used a feedback linearization method with a Proportional–Derivative controller to control the methyl ester concentration of the reactor. The reactor temperature, which is an important parameter in the production of biodiesel, was not considered. Hence, in the attempt to regulate both the methyl ester concentration and reactor temperature simultaneously for the CSTR biodiesel reactor, a multi-model adaptive control strategy was considered in the work of Mjalli et al.[1] The controller, although successful compared with conventional controllers, needed considerable amount of work to develop the model bank. To overcome this, the process was first modeled offline using a black-box Artificial Neural Network (ANN) modeling method and later was linearized online for the purpose of controller design.[7] The downside of this method, however, is that an offline ANN model needs to be developed in advance. This was alleviated by using the Recursive Least Squares (RLS) algorithm to model the process online for the purpose of retuning the Internal Model Controller.[8] The RLS-based controller, despite exhibiting good performance, showed unsatisfactory controller movements. To further improve the performance of RLS-based controllers, Ho et al.[9] used a Two-Inputs Two-Outputs centralized adaptive predictive controller where the internal model required by the Generalized Predictive Control (GPC) controller[10,11] was estimated by using a multivariable RLS algorithm[12,13]. Although this scheme (hereafter referred to as CRLS-GPC) produced good process responses and controller moves because of the more accurate representation of the process dynamics, the number of parameters (Np) to be estimated increase significantly with every additional pair of input and output process variables (e.g. Np~nT2 if the number of total plant inputs mT=number of total plant outputs nT). In this work, an alternative to the CRLS-GPC is proposed, where decentralized RLS schemes can be used to model the multivariable process as multiple Single-Input Single-Output models, each representing an individual loop. This would reduce the number of the parameters to be estimated (e.g. Np~nT under the same assumptions as stated previously) and the computational burden. Figure 1

*Correspondence to: Farouq Mjalli, Chemical Engineering, Sultan Qaboos University. E-mail: farouqsm@yahoo.com
shows the design of the control loops on the biodiesel reactor with such a scheme, which will be denoted as DRLS-GPC in this communication. Because both the DRLS-GPC and CRLS-GPC schemes share the same theoretical framework, this paper focuses on the main differences in formulation and results that present the DRLS-GPC scheme as an attractive alternative to the CRLS-GPC scheme. The performance of the DRLS-GPC scheme is further compared with that of the conventional Proportional–Integral (PI) controller under noisy process environments.

**SALIENT DIFFERENCES BETWEEN THE CRLS-GPC AND THE DRLS-GPC SCHEMES**

In the work of Mjalli et al.,[1] it was reported that the coolant flow rate ($F_c$) showed a slight nonlinearity relationship with the controlled variables (reactor temperature $T$ and methyl ester concentration $C_{ME}$), whereas the reactant flow rate ($F_o$) had a highly nonlinear relationship with the controlled variables. Moreover, offline system identification showed dead time of varying magnitudes at different operating regions. Control loop pairing using the Relative Gain Array and Dynamic Relative Gain Array (Fig. 2) analyses suggested the pairs $F_c$–$T$ and $F_o$–$C_{ME}$ and revealed some degree of interaction between the two loops selected. The results of these analyses are shown here:

$$RGA : \begin{pmatrix} F_o \\ F_c \end{pmatrix} = \begin{pmatrix} C_{ME} & T \\ 0.9002 & 0.0998 \\ 0.0998 & 0.9002 \end{pmatrix}$$

(1)

In view of what was mentioned previously, the control of biodiesel reactors poses potential challenges even before the effects of modeling uncertainty, disturbances, and signal noise are included.

For a process with $n$ inputs $u(k)$, $n$ outputs $y(k)$, and a stochastic noise variable $v(k)$ with random distribution and zero mean, the general Multi-Inputs Multi-Outputs (MIMO) Controlled Auto-Regressive Integrated Moving Average model required in the GPC is given by:

$$a(z^{-1})y(k) = b(z^{-1})u(k) + T(z^{-1})v(k) \frac{1}{1-z^{-1}}$$

(2)

In Eqn (2), $k$ is a positive integer that denotes the sampling instance, $k=0, 1, 2, \ldots$, whereas $T(z^{-1})$ is a design polynomial matrix[10,11,14] that is selected as the identity matrix $I$ here for simplicity. Defining $\alpha$ and $\beta$ as known positive integers, $a[n \times n]$ and $b[m \times n]$ are polynomial matrices in the $z$-domain given by:

$$a(z^{-1}) = I + \sum_{i=1}^{\alpha} a_i z^{-i}$$

(3)

$$b(z^{-1}) = \sum_{i=1}^{\beta} b_i z^{-i}$$

(4)

where $a_i, i = 1, \ldots, \alpha \in \mathbb{R}^{n \times n}$ and $b_i, i = 1, \ldots, \beta \in \mathbb{R}^{n \times m}$.

The selection of $\alpha$ and $\beta$ values should be based on considerations that a too high model order introduces additional computational complexities, whereas a low-order model gives a poor description of processes with dead time.[15] Although Ho et al.[9] used values of $\alpha = \beta = 1$ for the CRLS-GPC, these values were not practical for the DRLS-GPC because of the low model order. Because no a priori information on the dead time of the process is available, a second-order model is a good compromise. For a fair comparison, both schemes shall adopt the values of $\alpha = \beta = 2$. In this case, the coefficient matrices $a_{i=1,2} \in \mathbb{R}^{2 \times 2}$ and $b_{i=1,2} \in \mathbb{R}^{2 \times 2}$
of the CRLS-GPC scheme contain altogether 16 elements to be estimated recursively by the Variable Forgetting Factor RLS (VFF-RLS) algorithm.\cite{16} The DRLS-GPC scheme, on the other hand, only requires each VFF-RLS algorithm to estimate recursively four parameters for every loop. Specifically, the coefficient matrices are

$$a(z^{-1}) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} a_1 & 0 \\ 0 & a_2 \end{bmatrix} z^{-1} + \begin{bmatrix} a_3 & 0 \\ 0 & a_4 \end{bmatrix} z^{-2}$$ \hspace{1cm} (5)

$$b(z^{-1}) = \begin{bmatrix} b_1 & 0 \\ 0 & b_2 \end{bmatrix} z^{-1} + \begin{bmatrix} b_3 & 0 \\ 0 & b_4 \end{bmatrix} z^{-2}$$ \hspace{1cm} (6)

In both the CRLS-GPC and the DRLS-GPC schemes, the sampling time, the dimensionless tuning constants $\sigma$ and $C$, time elapsed before the activation of VFF-RLS and then GPC were identical to the work of Ho et al.\cite{9} A small amount of white noise with zero mean and variance of 0.0001 was added to the data of the process outputs entering the RLS algorithm to ensure persistence of excitation.\cite{17} In addition, only models with stable poles are implemented in the controller. As for the controller tuning parameters, the prediction horizon ($N$), the control horizon ($M$), the weights for the output residuals ($W$), and the move suppression weights ($R$) for both schemes were tuned according to the general guidelines given by Rossiter\cite{18}, and are given next:

**CRLS-GPC:**

$$N = 14; M = 6; W = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}; R = \begin{bmatrix} 0.0055 & 0 \\ 0 & 0.0035 \end{bmatrix}$$ \hspace{1cm} (7)

**DRLS-GPC:**

$$N = 10; M = 6; W = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}; R = \begin{bmatrix} 0.0035 & 0 \\ 0 & 0.0055 \end{bmatrix}$$ \hspace{1cm} (8)

Similar constraints on limits of flow rates and rate of change were imposed as follows:

$$\begin{align*}
3\% & \leq F_{c}(k) \\
97\% & \geq F_{o}(k)
\end{align*}$$ \hspace{1cm} (9)

$$\begin{align*}
-5\% & \leq \Delta F_{c}(k) \\
5\% & \geq \Delta F_{o}(k)
\end{align*}$$ \hspace{1cm} (10)

**RELATIVE PERFORMANCE OF THE CRLS-GPC AND THE DRLS-GPC SCHEMES**

In the simulations, practical values for each process parameter for a typical biodiesel reactor were selected. The set-point changes were more frequent than practice chiefly to challenge the controllers under worst case scenarios.

Figures 3 and 4 show the performance as well as the controller moves of both schemes in tracking successive set-point changes in opposite directions for the $C_{\text{ME}}$ and $T$ loops. From the figures, the performance of the DRLS-GPC scheme was not inferior to the performance of the CRLS-GPC scheme, even though the VFF-RLS parameter estimation scheme adopted was not multivariable in nature, but rather a decentralized one. The control performance shown in Table 1 for the last four set-point changes for both loops (the profiles for the first set point change were not considered because the VFF-RLS algorithm had yet to stabilize at the onset of simulation\cite{9}) further showed that there
were no remarkable improvements/differences for the average values of overshoot, rise time, and settling time of the CRLS-GPC over the DRLS-GPC scheme. Both control schemes were able to track the set-point changes efficiently for both loops.

The extent of the process interactions is most clearly observed in Fig. 3. The spikes in $C_{ME}$ in between set-point changes were due to changes in the set point of $T$. Such loop interaction effects for both control schemes were reasonably small and of similar order of magnitudes. On closer scrutiny, the magnitudes of the spikes, which reflected the strength of the loop interaction, were slightly larger for the CRLS-GPC scheme than those of the DRLS-GPC scheme (particularly at the onset of simulation), implying that the latter is more adept in handling loop interactions. On this counter-intuitive behavior, we suspect that the CRLS-GPC, in its effort to account for the multivariable dynamics of the process when computing optimized control moves, achieved smooth controller moves for both loops at the expense of larger effect of loop interactions. In contrast, because of its inability to account for the dynamics of the other loop, the DRLS-GPC was more aggressive, reducing the effects of loop interaction better resulting in slight oscillatory controller moves and the $T$ profile. For the $T$ loop (Fig. 4), however, the effect of set point changes in $C_{ME}$ was hardly noticeable.

On the quality of the controller moves, other than the slight oscillatory controller moves for the $T$ loop discussed previously, there was no significant performance difference in between the control schemes, as depicted by Figs. 3 and 4. Actuator saturation was not encountered, and the actuator moves produced by both schemes were generally non-aggressive, for both the $C_{ME}$ loop and the $T$ loop.

Figure 5 shows the $T$ loop prediction errors for the CRLS-GPC and the DRLS-GPC schemes. Although the performance of both the CRLS-GPC and the DRLS-GPC schemes in controlling the reactor temperature was almost identical, the variability between the prediction errors from both schemes was quite different. A more strongly fluctuating prediction error for the $T$ loop was observed in the DRLS-GPC scheme, although the fluctuations remained within approximately $\pm 0.05$ K. For the CRLS-GPC scheme, the corresponding prediction error had a noticeably smoother trend, but such improved accuracy did not result in a superior controller performance over the DRLS-GPC scheme. The $C_{ME}$ loop prediction errors (not shown) exhibited similar trends to the $T$ loop prediction errors, except that the pattern of fluctuations in the DRLS-GPC prediction errors was not noticeably different from that of the CRLS-GPC. The smooth trends of the $C_{ME}$ prediction errors indicate good tracking performance of both schemes.

### Table 1. Quantitative comparison between the performance of the DRLS-GPC and CRLS-GPC schemes for the methyl ester concentration ($C_{ME}$) loop and reactor temperature ($T$) loop in tracking four consecutive set-point changes.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$C_{ME}$ loop</th>
<th>$T$ loop</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DRLS-GPC</td>
<td>CRLS-GPC</td>
</tr>
<tr>
<td>Overshoot (K)</td>
<td>Negligible</td>
<td>Negligible</td>
</tr>
<tr>
<td>Rise time (s)</td>
<td>633</td>
<td>627</td>
</tr>
<tr>
<td>Settling time (s)</td>
<td>633</td>
<td>627</td>
</tr>
<tr>
<td>IAE*</td>
<td>132 kmol/m$^3$</td>
<td>178 kmol/m$^3$</td>
</tr>
</tbody>
</table>

DRLS-GPC, decentralized recursive least squares-based generalized predictive control controller; CRLS-GPC, centralized recursive least squares-based generalized predictive control controller.

*Integral Absolute Error over 40 000 s with multiple set-point changes.
The results thus far show that the more sophisticated CRLS-GPC did not lead to remarkable improvements in the overall controller performance, as measured by the quality of set-point tracking, loops interaction handling, and smoothness of controller moves. Although the decentralized VFF-RLS in the DRLS-GPC scheme may not be able to capture the complete dynamics of a multi-variable process, results suggest that the optimization engine embedded in the GPC controller was able to compensate to a certain extent the shortcomings of the decentralized VFF-RLS structure, giving the DRLS-GPC scheme comparable performance with the CRLS-GPC scheme. In addition to what was mentioned previously, the execution time for both algorithms was recorded for several repetitions, where the CRLS-GPC on average took 30% more time to complete execution compared with the DRLS-GPC. This observation is in line with our previous discussion in the introduction section, where the deployment of the DRLS-GPC is computationally more efficient as compared with the CRLS-GPC.

By considering the relative simplicity of the DRLS-GPC scheme, it is further scrutinized for the efficacy in regulatory control. Four variables were identified as possible disturbance variables in the mechanistic transesterification model, viz. the triglyceride concentration ($C_{TGO}$), feed temperature ($T_O$), coolant inlet temperature ($T_{CO}$), and stirrer rotational speed ($N$). A 5% increment in the nominal value of a quantity chosen from $C_{TGO}$, $T_O$, $T_{CO}$, and $N$ was introduced at time = 40 000 s, following the set-point tests. Figure 6 shows the performance of the DRLS-GPC scheme in rejecting the various load disturbances. The DRLS-GPC scheme successfully rejected all the disturbances within reasonable time, bringing both $C_{ME}$ and $T$ back to their set points within 1000 s at the most.

The efficacy of the DRLS-GPC scheme was further tested for its ability to handle noise in the biodiesel reactor. White noise with zero mean and a typical signal to noise ratio of $5^{[19]}$ was added to the outputs of the process to simulate a noisy environment. The same set-point changes in the previous tests under non-noisy situations were imposed here. Under such conditions, the performance of the DRLS-GPC against that of a conventional PI controller was compared. The derivative mode of the controller was turned off because of poor performance (i.e. overly aggressive controller moves as a result of derivative action on noisy systems) obtained during preliminary simulations. The conventional PI controller was initially tuned by using the standard Ziegler–Nichols open-loop procedure followed by further fine-tuning on the basis of experience and actual control performance.

Figures 7 and 8 show the performance of the DRLS-GPC over the conventional PI controller for the $C_{ME}$ loop. Although the conventional PI controller was able to track the set-point changes with Integral Absolute Error (IAE) = $362 \text{ kmol/m}^3$ (i.e. a value that was close to that achieved by the DRLS-GPC, IAE = $347 \text{ kmol/m}^3$), the control quality exhibited by the DRLS-GPC was superior in that a lower value of IAE was achieved with much smoother controller moves. Similar trends (not
shown) were observed in the \( T \) loop. The results here clearly demonstrate the superiority of the DRLS-GPC scheme over the conventional PI scheme under noisy environments typical of actual processes.

**CONCLUSION**

An analysis on biodiesel reactor control reveals that the simpler DRLS-GPC scheme could rival the performance of the previously published CRLS-GPC scheme.\(^9\) Especially in the initial stages, the larger number of parameters to be estimated made the latter sluggish. Further into time, the performance of both schemes remained on par when subjected to set-point changes involving process interaction. The controller moves required were also reasonable and without saturation. However, compared with CRLS-GPC, the DRLS-GPC gave model prediction errors that fluctuated more wildly (in the \( T \) loop), albeit within a similar range. Such behavior, nevertheless, did not impair its capacity to regulate the transesterification process studied.

Furthermore, the DRLS-GPC scheme displayed good disturbance rejection in regulatory control as well as performing under a noisy environment. It was clearly superior to a well-tuned conventional PI controller. For complex nonlinear processes as studied in this work, instead of deploying the much more computationally intensive CRLS-GPC scheme, the comparatively lighter DRLS-GPC could be an excellent compromise between complexity and performance.

**Acknowledgments**

The authors acknowledge the financial support from the UMRG grant RG065/09SUS and the PPP grant PS058/2009A, both by the University of Malaya.

**REFERENCES**


