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Evolutionary algorithm-based model predictive control for a reactive distillation column in biodiesel production

M. Manimaran[a], S. Nagalakshmi[b*], S. Vasanthi[c] and N. Muthukumar[d]

[a]Department of Electrical and Electronics Engineering, Sethu Institute of Technology, Virudhunagar, India; [b]Department of Electrical and Electronics Engineering, Sir Issac Newton College of Engineering and Technology, Nagapattinam, India; [c]Department of Electrical and Electronics Engineering, University College of Engineering, Dindigul, India; [d]Ramco Systems Limited, Chennai, India

ABSTRACT
Biodiesel is touted to be an alternative to the fossil fuels as it is conducive to the environment. This investigation proposes a control framework to produce biodiesel in a reactive distillation column via a transesterification process. To extract quality product, the temperature profile must be maintained along the column as per the requirements. However, constant interactions among the products inside the column disturb the temperature profile and consequently the product quality. Therefore, this investigation treats the process as a single input and single output system, where in the process interactions are modelled as disturbances. A model predictive controller (MPC) is designed for the proposed system to ensure product quality. The MPC parameters must be selected appropriately to ensure optimal performance. In this regard, to tune the MPC parameters optimally, we use two evolutionary algorithms namely, the real coded genetic algorithm (RGA) and the bio-geography based optimization algorithm (BBO). The results indicate the proposed control strategy provides offset free set point tracking when compared to the multivariable control strategy employed using the MPC algorithm. Among the two evolutionary controllers used for tuning the MPC parameters, the RGA MPC controller provides a satisfactory performance.

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BBO-MPC; RGA-MPC; conventional MPC; biodiesel; reactive distillation column

1. Introduction

In the last decade, the biofuels have emerged as a viable alternative to the crude-based fuels. Biofuels are renewable energy resources made up of fatty acid methyl esters (FAME), obtained from combining triacylglycerol present in vegetable oils or fats with methanol and catalysts through transesterification process [1]. The advantages of biofuel over the crude based fuels are: (i) it can be extracted from the domestic sources such as vegetable oils, (ii) Reduces the net carbon dioxide emissions up to 78% the crude based fuels, (iii) it is environmental friendly due to its biodegradable and non-toxic nature, and (iv) it improves the exhaust emissions in the engine [2]. Albeit these advantages, the transesterification process is energy intensive and expensive. The traditional method to extract biofuel involves a reactor unit to perform transesterification and an extraction unit to recover excess methanol from the biofuel. Consequently, it increases the production cost, and consumes energy to extract biofuel. Recent developments in biofuel extraction use a reactive distillation column as it combines the reaction and extraction process into a single unit, thereby significantly reducing the capital cost and energy consumption. However, performing transesterification and extracting excess methanol simultaneously is challenging due various factors such as fluctuations in the column temperature, variations in the feed, reflux ratio, reboiler duty, etc. Therefore, an advanced control strategy is to ensure desired product quality, minimize energy consumption and increase product throughput.

Several studies on extracting biofuel using reactive distillation columns are focused on the selection of reactants, design calculations to reduce the capital costs and the energy requirements. The authors in [3] investigated the biofuel extraction from the lauric acid and 2-ethyl hexanol. Biofuel production from the lactic acid and n-butanol is investigated in [4]. Investigations into biodiesel extraction in reactive distillation column that enable transesterification process are reported in [5,6]. Mueanmas et al. [7] investigated the feasibility of bio-fuel production in a reactive distillation column using Aspen Plus simulation software. They provided an optimal design and procedure for effective biodiesel extraction in terms of molar ratio of alcohol to oil, reboiler temperature, alcohol to feed location and

CONTACT M. Manimaran manimaran0101@gmail.com Department of Electrical and Electronics Engineering, Sethu Institute of Technology, Kariapatti, Virudhunagar 626115, Tamilnadu, India

*Present address: Department of Electrical and Electronics Engineering, Government Polytechnic College, Chekkanurani, Madurai, India.

reflux ratio for a reactive distillation column. A simple laboratory prototype is used to analyse and determine the optimal operating conditions for a reactive distillation column to extract biodiesel in [8]. Gaurav et al. [9] performed simulation analysis on the transesterification of triacylglycerol to FAME using a heterogeneous catalyst. Further, they concluded that the biofuel extraction using the reactive distillation column reduces the utility cost and the capital. Similarly, Boonanuwat et al. [10] designed and simulated four different biodiesel production process using a transesterification reaction between soybean oil and methanol in Aspen Plus software. They concluded that the usage of heterogeneous catalysts reduces the energy consumption. Although the above-mentioned investigations provide a benchmark on optimal design of distillation column, and the choice of reactants, the controller selection that ensures the desired product quality and production is given least priority. An excellent closed-loop control action is imperative to achieve the desired biofuel quality as the bio-diesel extraction in a reactive distillation column involves the transesterification process and excess methanol recovery in a single unit simultaneously. The poor control of column temperature in the face of external disturbances in reboiler duty, reflux ratio, etc., affects the product quality and increases the energy consumption significantly.

Notable works on designing control systems for producing biofuel in reactive distillation columns are available in the literature. The Proportional Integral and Derivative (PID) controller is used for biofuel extraction [11]. The authors use a traditional Ziegler Nicholas (ZN) tuning to tune the controller. The controller manipulates the reboiler duty to maintain the mole fraction of biodiesel. Similarly, a cascaded PID control configuration is proposed in [12,13]. The authors compare the conventional PID and the cascaded control to the performance of biodiesel extraction in a reactive distillation column. They conclude that the cascaded control configuration provides better product quality. Though the PID controllers are simple to design and inexpensive, they cannot effectively mitigate disturbance, and are ineffective in dealing with process nonlinearities. To overcome the limitations of PID, a fractional order PID controller is proposed in [14] to maintain the composition of biodiesel. Though these controllers can handle nonlinearities, they lack optimal performance. In recent years, several optimization-based controllers havebeen used to control the biofuel production in a distillation column, and in ref. [15], a steady state optimization method is implemented to ensure product quality in biofuel production. Here three optimization methods are used namely, Fletcher Reevs, Quasi-Newton and SQP algorithms. The investigation showed that the Fletcher Reevs provided economical results. A singular value-based decomposition is used to determine the sensitive trays for temperature control as executed in [16]. In recent years, advanced control strategies such as model predictive controllers (MPC) have been employed in biofuel production see, [17–19]. Unlike the traditional controllers, the MPC algorithm computes an optimal control input by solving an underlying optimization routine or cost function at every time instant. The advantages of MPC over the traditional controllers are (i) the ability to handle disturbances, (ii) the ability to incorporate process constraints and (iii) minimize the operation cost/control cost. Despite these advantages, designing MPC algorithms for a complex process such as reactive distillation column is challengeing due to the interactions among the process variables. A poor MPC control strategy leads to a tight control on one process variable and offsets in another. Therefore, designing MPC control strategy and optimal selection of the tuning process is essential to ensure product quality and minimize the operating costs. Considering the aforementioned factors, this investigation proposes a new MPC control configuration to extract biofuel in a reactive distillation column. The contributions of this investigation are:

(1) Departing from the traditional multivariable control structure, this investigation proposes a single loop control that controls the bottom tray temperature, and models the process interactions as disturbances.
(2) The weights associated with the MPC algorithm are optimally tuned using two evolutionary algorithms, Real coded Genetic Algorithm (RGA) and Biogeography based Algorithm (BBO).

This paper is organized into four sections. Section 2 outlines the biofuel production in a reactive distillation column. Section 3 describes the MPC design for a reactive distillation column and explains RGA and BBO algorithms to tune the MPC weights. Section 4 illustrates the performance of the proposed control configuration for biofuel production in a distillation column, and the concluding remarks are provided in section 5.

2. Process description

This section describes the biofuel extraction in a reactive distillation column, and presents its mathematical model to design the MPC algorithm. This investigation uses a combination of Jatropa oil and methanol mixture at 9:1 ratio with nano CaO as catalyst to produce biofuel using transesterification reaction. The experiment was performed in a pilot packet reactive distillation column. It contains a horizontal reboiler with variable heating capacity ranging from 0 to 5 kW at the bottom, and a reflux section that provides 0-100% reflux at the apex of the column. As the transesterification progresses in the column, the excess methanol collects at the apex as distillate, while the FAME is collected as the product at the bottom. To achieve good control over the biofuel quality, the bottom tray temperature must be maintained close to 80°C. However, it is affected by fluctuations in the reboiler duty and the reflux rate. To design an effective controller, a mathematical model is developed using the time series data containing top tray temperature, bottom tray temperature, reflux ratio and the reboiler duty. The proposed mathematical model is a state space representation containing two models: (i) process model and (ii) disturbance model.

2.1. Process model

It describes the dynamics related to the column temperature at the bottom and the reboiler duty. Here, the tray temperature is the controlled variable and the reboiler duty is the manipulating variable. The n4sid method is used to get the state space model that shows the relationship between the tray temperature and the reboiler duty as,

$$\underbrace{\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix}}_{x(k+1)} = \underbrace{\begin{bmatrix} 1.4921 & -0.4990 \\ 1 & 0 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix}}_{x(k)} + \underbrace{\begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{B} u(k)$$

$$y(k) = \underbrace{\begin{bmatrix} -0.0020 & 0 \end{bmatrix}}_{C} \underbrace{\begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix}}_{x(k)} \tag{1}$$

2.2. Disturbance model

It lumps all the process interactions that affects the temperature profile at the bottom of the column. This investigation considers the effect of the reflux ratio on the bottom tray temperature as disturbance.

$$\underbrace{\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix}}_{x_d(k+1)} = \underbrace{\begin{bmatrix} 1.6486 & -0.6540 \\ 1 & 0 \end{bmatrix}}_{A_d} \underbrace{\begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix}}_{x_d(k)} + \underbrace{\begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{B_d} r_d(k)$$

$$d(k) = \underbrace{\begin{bmatrix} -0.0166 & 0 \end{bmatrix}}_{C_d} \underbrace{\begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix}}_{x_d(k)} \tag{2}$$

The schematic of the MPC control configuration for biodiesel in a reactive distillation column is shown in Figure 1. In the following section, the MPC design using the evolutionary algorithms is discussed.

3. The MPC algorithm

The MPC is an advanced control technique that uses the process model to compute the future control input [20,21]. Because of MPC's inherent ability to handle disturbance, process variations, process constraints and nonlinear behaviour makes it is an excellent choice of control the reactive distillation column [22–27]. In what follows, the MPC design for the biofuel production in a reactive distillation column is provided.

The reactive distillation column is described as a discrete LTI system:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + d(k) \\ y(k) &= Cx(k) + Du(k) \end{aligned} \tag{3}$$

where $x \in \mathbb{R}^n$ is the system state, $u \in \mathbb{R}^m$ is the reflux rate (control input), $y \in \mathbb{R}^p$ is the top tray temperature (system output), $d \in \mathbb{R}^n$ is the system disturbance and A, B, C, D are system matrices with commensurate dimensions. The disturbance model $d(k)$ represents the effect of the reboiler duty on the top tray temperature, and it is described as,

$$\begin{aligned} x_d(k+1) &= A_d x_d(k) + B_d r_d(k) \\ d(k) &= C_d x_d(k) + D_d r_d(k) \end{aligned} \tag{4}$$

where $x_d \in \mathbb{R}^n$ is the state associated with the disturbance, $r_d \in \mathbb{R}^m$ is the reboiler duty, and A_d, B_d, C_d, D_d are the matrices associated with the disturbance model. The MPC uses the plant and disturbance model, and computes the future control moves for N_p time steps called prediction horizon. The control input is computed by solving a constrained quadratic optimization problem at each sampling instant and it is given by,

$$\begin{aligned} J = &\sum_{j=1}^{p}\sum_{i=1}^{N_p} \{w_{i,j}^{y}[r_j(k+i|k) - y_j(k+i|k)]\}^2 \\ &+ \sum_{j=1}^{m}\sum_{i=1}^{N_p-1} \{w_{i,j}^{u}[u_j(K+i|k)]\}^2 \\ &+ \sum_{j=1}^{m}\sum_{i=1}^{N_p-1} w_{i,j}^{\Delta u}\{[u_j(k+i|k) - u_j(k+i-1|k)]\}^2 \end{aligned}$$

$$\begin{aligned} &s.t. \\ &y_{\min} \le y(k) \le y_{\max} \\ &u_{\min} \le u(k) \le u_{\max} \\ &\Delta u_{\min} \le \Delta u(k) \le \Delta u_{\max} \end{aligned} \tag{5}$$

where k is the current sampling instant, $\{y_{\min}, y_{\max}\}$ are output constraints, $\{u_{\min}, u_{\max}\}$ are the input constraints and $\{\Delta u_{\min}, \Delta u_{\max}\}$ are the slew rate constraints. Further, $w_{i,j}^{y}$, $w_{i,j}^{u}$, $w_{i,j}^{\Delta u}$ are the MPC tuning parameters for the error term, control input and the slew rate. The appropriate selection of weights/

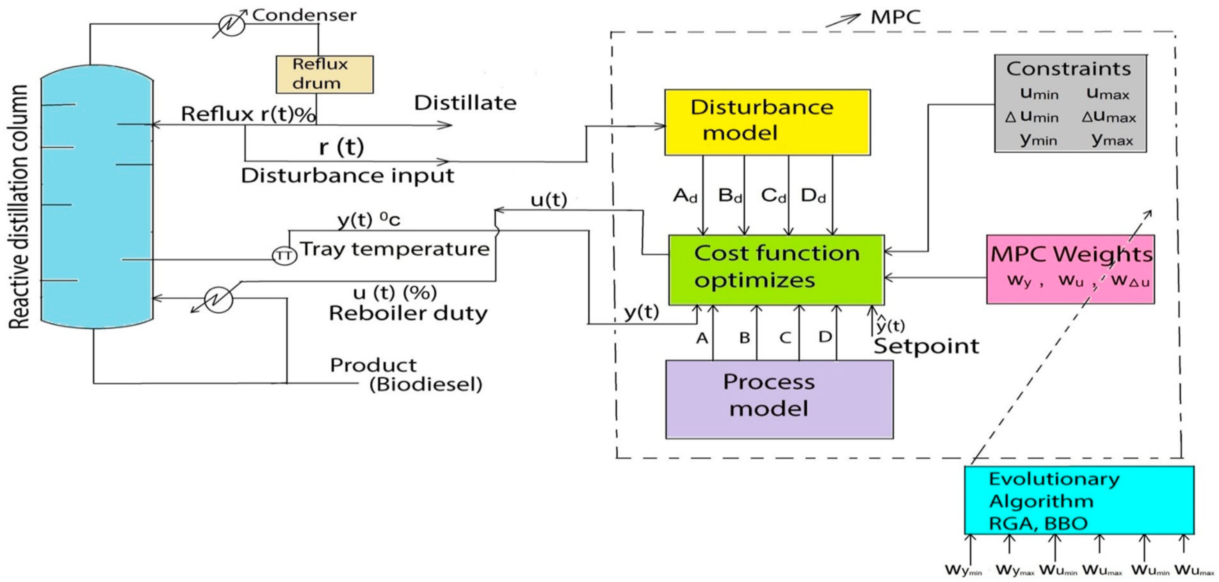

Figure 1. Schematic diagram of reactive distillation column.

penalization factors in the cost function is essential to achieve optimal control performance in MPC. This investigation uses two evolutionary algorithms namely, (i) Real coded genetic algorithm and (ii) Bio-geography algorithms for optimal weight selection. The procedure to determine the MPC weights using the above mentioned algorithms are discussed in what follows.

3.1. MPC weight tuning using real-coded genetic algorithm

The RGA algorithm is inspired from the principles of genetics and natural selection. The RGA is widely used to optimize different problems because it provides near global optimal solution. Figure 2 illustrates the RGA algorithm to tune the MPC weights. The algorithm starts with generating candid solutions known as population N_{pop} in a three-dimensional search space N_d. Each candid solution in N_{pop} is made to solve a fitness function f given by,

$$f = w_1 \int_0^t (r-y)^2 dt + w_2 \int_0^t |r-y| dt \tag{6}$$

The fitness function is a combination of the integrated squared error and integrated absolute error, where in the weights associated with these error terms are given by $\sum_{i=1}^{2} w_i = 1$. The candid solutions are ranked based on the highest fitness value and is given by,

$$p_i = \frac{f_i}{\sum_{i=1}^{N_{pop}} f_i} \tag{7}$$

where p_i is the probability of the candid solution getting selected. To further the optimal solution, the parent population is made to cross over to produce new offsprings, and it is given by,

$$O_i = \alpha p_i + (1+\alpha) p_{i+1} \tag{8}$$

where O is the offspring and α is the cross over rate. To change the search direction, and direct the solution towards global optimum, a small number of population is tweaked. This process is known as mutation. This process shifts the search for optimum solution to different parts of the search space.

3.2. MPC weight tuning using bio-geography based algorithm

The BBO algorithm works based on the biological distribution of the species in a habitat. Unlike the RGA algorithm, the BBO preserves the potential optimal candidate solutions in the current iteration to the next iteration, providing better global optimum solution. Figure 3 illustrates the BBO algorithm used to tune the MPC weights. The algorithm starts with mapping the candid MPC weights (species) to a habitat H with an immigration rate μ and emigration rate λ.

The candid solutions mapped to habitat is determined probabilistically as

$$\begin{aligned} P_s(t+\Delta T) &= P_s(t)(1-\lambda_s \Delta T - \mu_s \Delta t) \\ &\quad + P_{s-1}\lambda_{s-1}\Delta t + P_{s+1}\mu_{s+1}\Delta t \end{aligned} \tag{9}$$

where P_s is the probability of a species in a habitat. The emigration and immigration rate for a species in a habitat is determined as follows

$$\begin{aligned} \mu_k &= \frac{Ek}{n} \\ \lambda_k &= I\left(1-\frac{k}{n}\right) \end{aligned} \tag{10}$$

where E and I are the maximum immigration and emigration rates, respectively. Then the species are

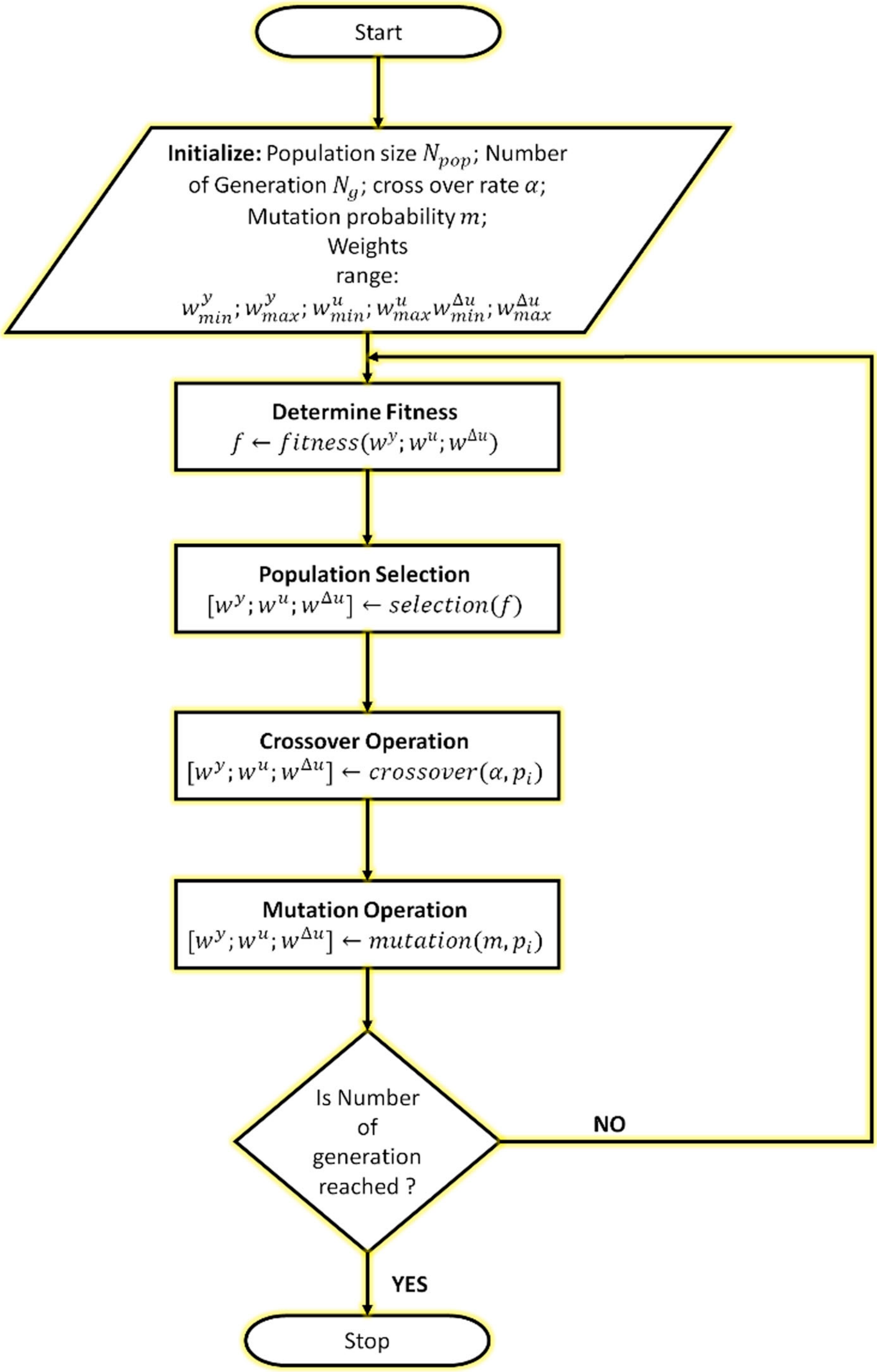

Figure 2. RGA algorithm to tune MPC weights.

evaluated for Habitat Suitability Index/ fitness function in () to find the optimal candid solution. The species are ranked based on the HSI, and the emigration and immigration rate of the elite species are updated. Furthermore, to achieve the global optimal solution, some species are migrated to the other habitats with a probability P_{mod}. Also, certain species in a habitat are mutated to find the new global optimal solution, and it is given by,

$$m(s) = m_{\max}\left(\frac{1 - P_s}{P_{\max}}\right) \tag{11}$$

where $m(s)$ is the mutation rate for the species s, $m_{\max}$ is the maximum mutation rate. The algorithm executes for the prescribed number of generations and yields optimal MPC weights.

4. Results and discussions

This section discusses the benefits of MPC weight tuning using the RGA and the BBO algorithms. The results are illustrated using the simulations performed in MATLAB/Simulink Software using a desktop computer with an Intel i5 processor 230 GHz clock speed

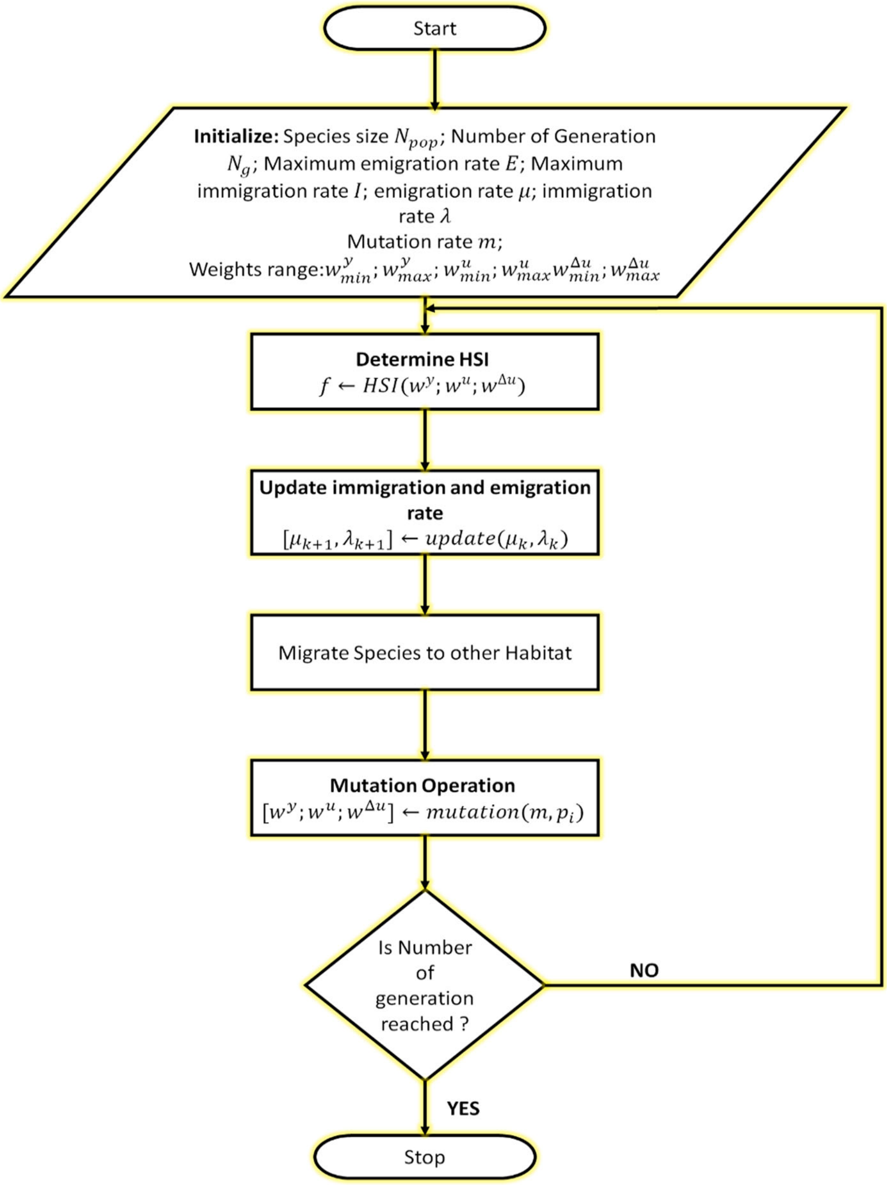

Figure 3. BBO algorithm to tune MPC weights.

and 4 GB RAM. The analysis focuses on MPC's ability to maintain product quality amidst various disturbances that arises due to fluctuations in the reboiler duty. Also, this investigation aims to illustrate the performance improvements obtained over manual MPC tuning, as against the proposed method.

As a first step, we tune the MPC algorithm manually with control input weights w^u, slew rate weights $w^{\Delta u}$ and output weights w^y as 1, 2.5 and 20, respectively. The aforementioned values are arrived after several trial and error. Next, the MPC weights are tuned using the RGA and BBO algorithm. To ensure uniformity in tuning procedure, the parameters such as population size, number of generations, mutation rate and crossover (in case of RGA) and migration rate (in case of BBO) are maintained identical across two algorithms. Table 1 lists the RGA and BBO parameters used to tune the MPC weights. The population size and number of generations are set to a default value of 20 units, while the mutation rate is set at 0.008. Also, the constraints on the MPC weights are similar in RGA and BBO algorithms. Table 2 illustrates the MPC weights obtained using the RGA and the BBO algorithms. It is observed that the BBO algorithm emphasizes the control input weights w^u more than the output weights w^y. This leads to offset free control with heavy penalization on control inputs.

Table 1. Parameters for RGA and BBO algorithms to tune MPC weights.

Parameters	RGA	BBO
Population size	20	20
No. of generation	20	20
Cross over rate	0.8	–
Mutation rate	0.08	0.08
Weights range on output w^y	[0 0.0002]	[0 0.0002]
Weights range on control input w^u	[0 0.00005]	[0 0.00005]
Weights range on slew rate $w^{\Delta u}$	[0 0.5]	[0 0.5]

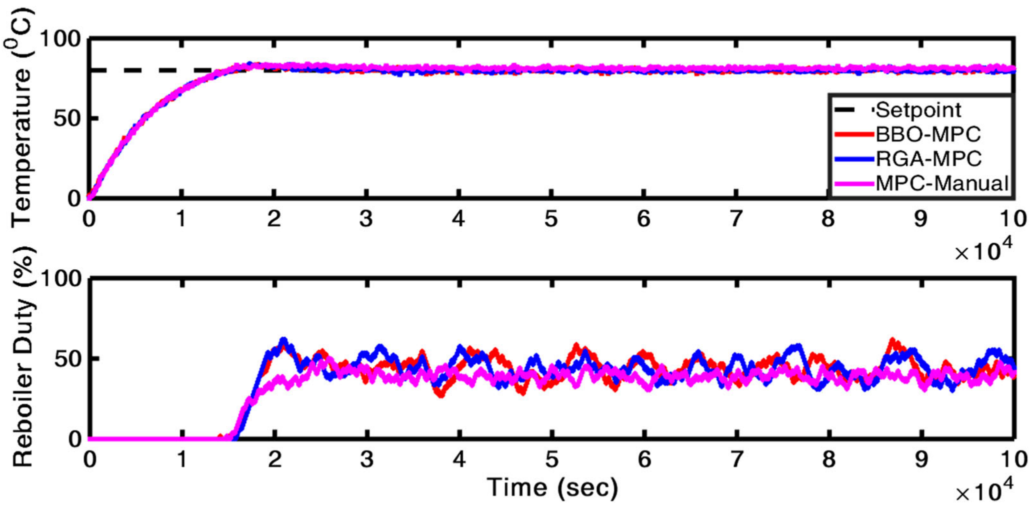

Figure 4. Bottom tray temperature and the reboiler duty obtained using BBO-MPC and RGA-MPC and manual MPC algorithms.

Table 2. MPC weights obtained using RGA and BBO algorithms.

Algorithm	w^u	$w^{\Delta u}$	w^y
RGA	5.48×10^{-5}	9.2079×10^{-7}	0.2204
BBO	4.31×10^{-6}	4.34×10^{-6}	0.45

Table 3. Transient characteristics obtained by BBO-MPC, RGA-MPC and Manual MPC algorithms.

Algorithm	Rise time (s)	Settling time (s)	Peak overshoot (%)
Manual-MPC	5573	22,241	5.2
RGA-MPC	5520	22,080	5.06
BBO-MPC	5570	22,200	5.17

4.1. Tracking performance

This section discusses the tracking performance obtained by the RGA-MPC and BBO-MPC. To maintain the distillate quality, the controller is required to maintain the bottom tray temperature at 75°C. Furthermore, a white Gaussian noise is introduced in the simulations to account for the sensor noises that occur in the practice. Figure 4. illustrates the transient response and the control effort expended by the RGA-MPC and BBO-MPC algorithms. It is observed that both algorithms provide identical transient responses. However, the transient characteristics listed in Table 3 shows that the RGA-MPC algorithm performs better than the BBO-MPC algorithm. The RGA-MPC improves the rise time by 0.89%, settling time by 0.54%, and peak overshoot by 2.29%. This is due to improved penalization of the control input by the BBO algorithm than the RGA. When compared with the manual MPC algorithm, both the BBO and RGA based controllers provided improved performance up to 0.1–0.9%.

The controller performances are validated using four performance metrics namely, (i) Integral Absolute Error (IAE), (ii) Integral Squared Error (ISE), (iii) Integral Time-weighted Absolute Error and (iv) Integral Time-weighted Squared Error (ITSE). The IAE penalizes the errors in the steady state. At the same time, the ISE penalizes the errors in the transient stages. The metrics ITAE and ITSE penalizes the errors in the steady state and the transient stages over a period of time. From Table 4, it is observed that the BBO-MPC improves ISE by 1.784% than RGA and 1.1% than manual-MPC, while the RGA-MPC improves the IAE by 0.98% than BBO and 43% than the manual MPC, ITAE by 6.53% and ITSE by 7%. This indicates that the RGA-MPC provides better control performance that the BBO-MPC algorithm and manual MPC.

Table 4. Controller performance obtained for setpoint tracking using BBO-MPC, RGA-MPC and Manual MPC algorithms.

Algorithm	IAE	ISE	ITAE	ITSE
Manual-MPC	3.58	65.01	520,740	1,934,500
RGA	2.028	58.27	153,230	336,020
BBO	2.048	57.23	163,236	361,340

4.2. Disturbance rejection

This section discusses the disturbance rejection performance of BBO-MPC and RGA-MPC algorithms. The load disturbance is introduced by varying the reflux ratio in the simulations. They are (i) a step change in the reflux rate and (ii) an impulse change in the reflux rate. To achieve optimal product quality, the bottom tray temperature column must be maintained at 80°C. However, due to fluctuations in the reflux rate, the bottom tray temperature tends to shift from 80°C, affecting the product quality, significantly.

As a first step, Figure 5. illustrates the BBO-MPC and RGA-MPC responses for a twofold step change in the reflux ratio with magnitude 32% and 28% is introduced at 90,000 and 180,000 s, respectively. It is observed that the RGA-MPC effectively eliminates the effect of reboiler duty in the tray temperature than the BBO-MPC algorithm, while the manual MPC tuning suffers to mitigate the disturbance. Also, from the control performance reported in Table 5, the RGA-MPC

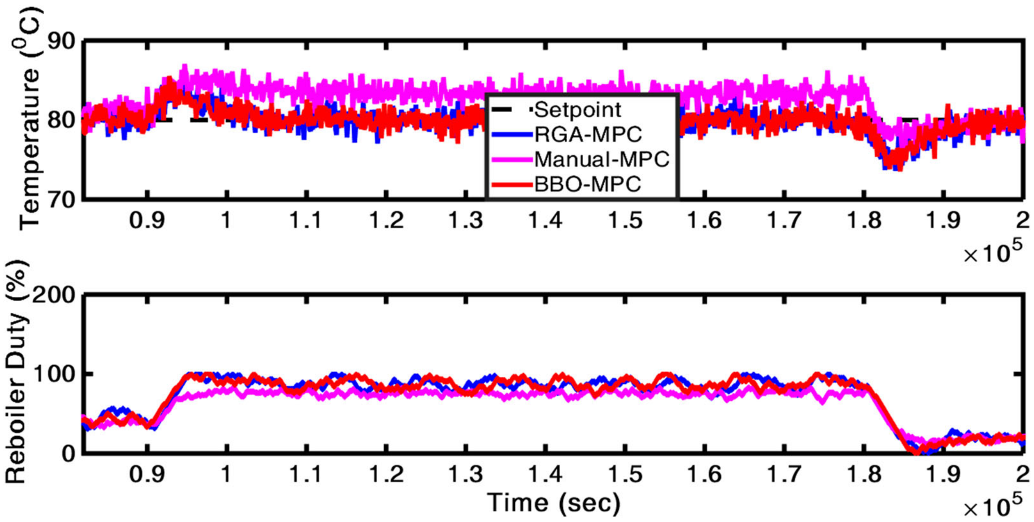

Figure 5. Load disturbance rejection profile for a step change in the reboiler duty using BBO-MPC, RGA-BBO and Manual MPC algorithms.

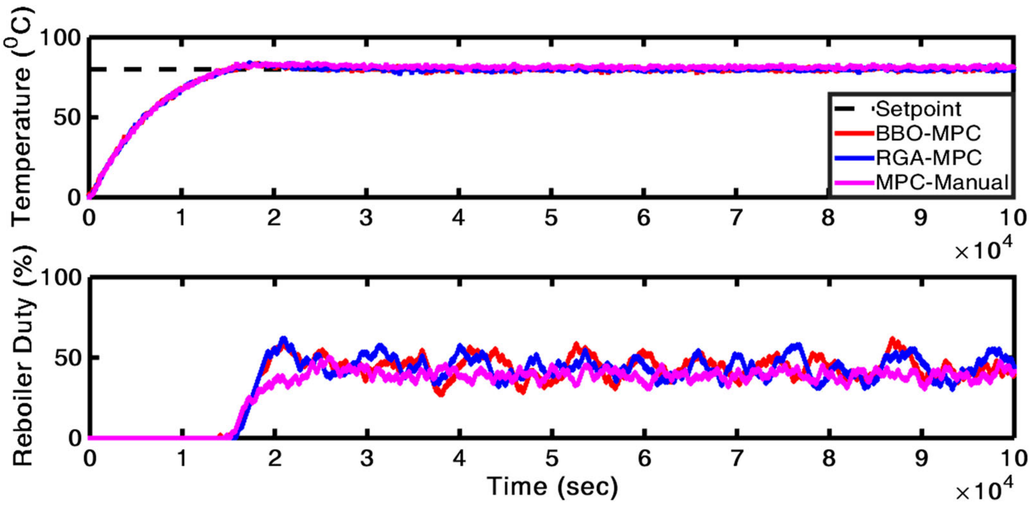

Figure 6. Load disturbance rejection profile for an impulse change in the reboiler duty using BBO-MPC, RGA-MPC and Manual MPC algorithms.

Table 5. Controller performance obtained by BBO-MPC, RGA-MPC and Manual MPC algorithms for step change in the reboiler duty.

Algorithm	IAE	ISE	ITAE	ITSE
Manual-MPC	2.89	61.83	264,720	805,180
RGA-MPC	2.1153	58.84	16,878	41,462
BBO-MPC	2.1447	58.54	17,382	42,585

Table 6. Controller performance obtained for an impulse change in the reboiler duty using BBO-MPC, RGA-MPC and Manual MPC algorithms.

Algorithm	IAE	ISE	ITAE	ITSE
Manual-MPC	3.5846	64.95	520,440	1,925,200
RGA-MPC	2.0926	58.33	16,725	39,204
BBO-MPC	2.0782	58.56	16,423	37,457

improves the IAE by 1.37%, ITAE by 2.89% and ITSE by 2.63%. This indicates that the RGA-MPC algorithm is best suited to reject any step change in the reflux ratio.

To further analyse the disturbance rejection ability, the reflux ratio is increased to 34% from 30%. Figure 6. illustrates the responses obtained by BBO-MPC and RGA-MPC algorithms. Both algorithms provide a similar rejection characteristics. However a close observation on the controller performance in Table 6 shows that the BBO-MPC algorithm provides improvements up to 0.6% in IAE, 1.8% in ITAE and 4.45% in ITSE. This shows that the RGA-MPC algorithm performs better for a sudden change in reflux ratio, then the BBO-MPC algorithm.

5. Conclusion

This present work proved that reactive distillation backed with Jatropa oil with nano CaO is a hopeful method for the continuous biodiesel production. The closed loop system of an RD for a Biodiesel production Conventional MPC and RGA-MPC, BBO- MPC two evolutionary algorithms are investigated. RGA-MPC provides best optimal performance in set point tracking method (IAE 0.98%, ITAE 6.53%, ITSE 7%) and step response method (IAE 1.37%, ITAE 2.89%, ITSE 2.63%). In case of BBO –MPC compared to RGA-MPC it's provide better performance in Impulse response (IAE 0.6%, ITAE 1.8%, ITSE 4.45%). In our proposed analyses shows that tuning of MPC using two evolutionary algorithms provided better performance than the Conventional MPC. It was indicated that the RD was well handled by the RGA –MPC used under set point tracking it was able to get settled desired temperature with in stipulated time.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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