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A Novel Exergy-Based Optimization Approach in Model Predictive Control for Energy-Saving Assessment

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Abstract
Nowadays, in many industrial applications, energy management is recognized as an essential issue. Comprehensive understanding of exergetic perspectives can help save more resources. A unique exergy-based optimization approach in model predictive control (MPC) framework is introduced in this paper to scale back Total Destroyed Exergy (TDE) of the controlled process. The proposed MPC facilitates the capability to address both the process and energy constraints in a multiple-input multiple-output (MIMO) system. To this end, the new MPC cost function is presented to unravel an optimal control problem supported TDE reduction and acceptable control performance to improve energy conservation. The findings will be demonstrated through a case study of industrial alkylation of benzene process to assess the effectiveness of the proposed energy-saving approach, which meets control performance needs.

Keywords Exergy analysis · Optimization · Model predictive control · Energy saving · Energy efficiency · MIMO system

1 Introduction

The energy utilization plays a vital role in many industrial applications, and considerable effort is made to make energy usage more recyclable, economical, effective, and clean. Thermodynamic rules govern energy utilization, and a decent understanding of exergetic perspectives can help recognize sustainable energy options (Marty et al. 2019). Exergy analysis has been introduced within the literature as a useful tool for an energy assessment. Luyao et al. (2017) have employed exergy analysis for the economic evaluation of the steam superheat utilization using regenerative turbine in ultra-supercritical power plants under design/off-design conditions. Gutiérrez and Vandecasteele (2011) presented an evaluation methodology by implementing two new exergy-based metrics for the calcination process thanks to decreased energy consumption. Ahmadi et al. (2012) researched thermodynamic modeling and exergy and environmental analyses alongside the optimization of polygeneration energy supplies for electricity, cooling, heating, and hot water. A replacement model for predicting the particular chemical exergy of municipal solid waste (MSW) has been established in Eboh et al. (2016), where the model was based on the content of carbon, hydrogen, oxygen, nitrogen, sulfur, and chlorine on a dry ash-free.

Model predictive control (MPC), on the other hand, is often considered to be one of the most distinguished control strategies identified within the literature, dealing with constrained MIMO systems (Hadian et al. 2015; Hadian et al. 2014, 2019; Salahshoor and Hadian 2014). The optimizer is the central part of MPC strategy, seeking for an economic response, subjected to real-world constraints. The optimization problems mainly described by an objective function, which contributes to a cost-effective solution while holding the process variables within reasonable limits. Optimiza-

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tion algorithms, namely classical or metaheuristic, have been extensively used in control applications, ranging from to PID (Shahbazian 2015; Hadian et al. 2019) and fuzzy logic controller (Fard et al. 2016) to MPCs, to improve robustness, identification and stability. Whidborne et al. (2003), as an example, did an excellent review of Optimization applications in control engineering, exclusively focused on the PID controller. On the subject of MPC, similar research works, whether through single (Hadian et al. 2015; Salahshoor and Hadian 2014) or multi-objective functions, have been carried out. The importance of generic optimization can be perfectly demonstrated in Wang and Boyd (2009), where the controller overcomes slow dynamics. A CSTR with a nonlinear model is controlled with a group of optimized MPC to measure the performance of various strategies in terms of feasibility region and computational load. A multi-objective optimization technique is presented for MPC strategy in Wojsznis et al. (2007) that guarantees three essential criteria of MPC control and optimization simultaneously: (a) constraint handling, (b) economic optimization, and (c) control functionality. In an identical approach, Ju et al. (2000) solved a nonlinear MPC problem by employing a NARX model using. In our previous study (Hadian et al. 2014), an event-based MPC has been proved to reduce energy and computation load in which energy consumption is analyzed with exergy. Notwithstanding prior research, to the best of our knowledge, the optimization approach within the MPC framework has been introduced for the first time to address the entire exergy destruction of the controlled process to realize maximum control efficiency subject to constraints. An MPC with multi-objective cost function is developed in this paper in which mean-square error (MSE) and total destroyed exergy (TDE) are designated for stability and economic factors, respectively.

In this paper, a novel optimization approach is introduced for MPC to contemplate the exergy losses of the whole process combined with control objectives with constraint handling. The proposed method is implemented on a catalytic alkylation of benzene process to validate the desired system performance for the new MPC strategy based on energy assessment.

The rest of the paper is arranged as follows: Approach will be discussed in Sect. 2. Section 3 presents case studies, and Sect. 4 illustrates the results and discussion.

2 Approach

The concept of the new optimizer will be described in the following section. The conventional cost function for MPC is so designed to form the control system output(s) following the appropriate value referred to as output(s) set-point while considering control input(s) and control output(s) constraints. This method has been known as one of the best control strategies with excellent performance among the control approaches. However, in some practical case studies, energy-saving takes a crucial role as well as control performance, and consequently, it needs to be considered in the cost function. An intelligent tradeoff between control performance and energy saving could be a useful way to meet this goal. Exergy is introduced in Sect. 2.1 as a critical concept, which makes us able to concentrate on the energy-saving aspect; the more destroyed exergy reduction is, the more energy is saved. The main contribution is made by this paper is to take into account exergy reduction as a new system output added to the desired system output(s). The new cost function will be described so as to make use of this new economic output.

2.1 Exergy

Exergy is described as a valuable part of total energy which could be converted into work equally in a suitable condition. Exergy analysis is conventionally wont to indicate thermodynamic efficiency of the process, emphasizing on all materials and energies quality losses (Calli et al. 2019). Exergy analysis is known as a practical method to understand what proportion of wasted energy could be recycled if the required measure is hired. Consistent with the concept of energy, the exergy of a stream is dependent on the given reference environment condition. This paper uses the reference environment condition defined by Szargut et al. (1987), meaning $T_0 = 298.15$ K, $P_0 = 101.325$ kPa (i.e., 1 atm). Chemical exergy, physical exergy, and mixing exergy are three kinds of exergy, which are included in the all fluid stream (Luyao et al. 2017). The chemical exergy of a material stream $\dot{X}_{\text{ch}}$[kW] is calculated using the standard chemical exergy for component i, denoted by $e^0_{\text{ch},i}$ [kJ/mole], and molar flow of component i, shown by $\dot{F}_i$ [mole/s], and then the summation of all present components in the stream (Luyao et al. 2017):

$$\dot{X}_{\text{ch}} = \sum_{i=1}^{N} \left(\dot{F}_i e^0_{\text{ch},i} \right) \tag{1}$$

where N is the number of components.

The physical exergy, also known as thermomechanical exergy, of a stream $\dot{X}_{\text{ph}}$ [kW] is calculated by the difference between work done in process conditions (T, P) and the one done in the reference conditions (T_0, P_0) (Luyao et al. 2017):

$$\dot{X}_{\text{ph}} = \left[\sum_{i=1}^{N} \left(\dot{F}_i h_i \right) - \sum_{i=1}^{N} \left(\dot{F}_{0,i} h_{0,i} \right) \right] - T_0 \left[\sum_{i=1}^{N} \left(\dot{F}_i s_i \right) - \sum_{i=1}^{N} \left(\dot{F}_{0,i} s_{0,i} \right) \right] \tag{2}$$

where h_i and s_i represent the molar enthalpy and entropy of component *I*, respectively. The mixing exergy, denoted by $\dot{X}_{\text{mix}}$ [kW], is equal to the difference of mixture exergy at process conditions (T, P) and the exergy of component *i* (Luyao et al. 2017):

$$\dot{X}_{\text{mix}} = \left[\dot{F}h - \sum_{i=1}^{N}(\dot{F}_i h_i)\right] - T_0\left[\dot{F}s - \sum_{i=1}^{N}(\dot{F}_i s_i)\right] \tag{3}$$

where h and s are the molar enthalpy and entropy of the mixture, in succession. The total exergy of a stream, denoted by $\dot{X}_{\text{tot}}$ [kW], at process conditions (T, P) is given as:

$$\dot{X}_{\text{tot}} = \dot{X}_{\text{ch}} + \dot{X}_{\text{ph}} + \dot{X}_{\text{mix}} \tag{4}$$

Subsequently, by rewriting an exergy formulation of the second law of thermodynamics for control volume, the destroyed exergy of a chemical process is achieved as Cangel and Boles (2002)

$$\dot{X}_{\text{destroyed}} = \dot{X}_{\text{tot,in}} - \dot{X}_{\text{tot,out}} - \dot{W} + \dot{Q}\left(1 - \frac{T}{T_0}\right) \tag{5}$$

where $\dot{W}$ is work done on the process, $\dot{Q}$ is the amount of heat entering the process, T is process temperature and T_0 is reference environment temperature. Every attempt to reduce $\dot{X}_{\text{destroyed}}$ will result in more energy-saving, and gain more economic advantages.

2.2 MPC Cost Function

MPC cost function is designed in this section to achieve optimal control law in the company of minimized TDE. This objective function solves the optimization problem online under process constraints in which a combination of the control and energy components that are defined as follows:

$$\text{minimize } \boldsymbol{F}(x) \tag{6}$$

$$\boldsymbol{G}(x) \leq 0, \; i = 1, 2, \ldots, m \tag{7}$$

$$\boldsymbol{F}(x) = [f_1(x) \; f_2(x)] \tag{8}$$

$$\boldsymbol{G}(x) = [g_1(x) \; g_2(x)] \tag{9}$$

where $\mathbf{x} = [x_1, x_2, \ldots x_n]$ are state variables, $F(x)$ is the objective function (also called cost function), $G(x)$ includes constraints regarding whether the process and economic limitations, n is the number of optimization state variable or optimization variables, m is the number of constraints, $f_1(x)$ is associated with an energy cost function, $g_1(x)$ is associated with energy constraints, and $f_2(x)$ is related to control cost function and $g_2(x)$ is related to process constraint. The number of optimization variables and inequality constraint equations is also indexed by two parameters n and m. The aim is to minimize both objective functions $f_1(x)$ and $f_2(x)$ with respect to variables x subjected to the constraints $g_1(x)$ and $g_2(x)$ to attain both energy and control goals.

With a linear combination of energy and control cost function, the given multi-objective cost function is employed subjected to linear inequality constraints:

$$\begin{aligned} &\min w_1 f_1 + w_2 f_2 \\ &G(x) \leq 0 \end{aligned} \tag{10}$$

where w_1 and w_2 are weighting coefficients; the more the w_1 is, the more urgent is the minimization of energy loss and similarly the more the w_2 is, the more urgent is the minimization of control desires, including transient and steady-state responses. The mathematical equations of f_1 and f_2 can be found in the next section. The fundamental distinction of the current controller is to determine the optimum control actions, while less energy is destroyed, measured by the amount of exergy destroyed.

3 Case Study

3.1 Process Description

Alkylation of benzene with ethylene, a principal process in the petrochemical industry, produces ethylbenzene. As shown in Fig. 1, the process studied in this work consists of four continuously stirred tank reactors (CSTRs) and a flash tank separator. A detailed description of the process is widely described in Salahshoor and Hadian (2014), Ganji et al. (2004) and Liu et al. (2010). Since the process is nonlinear, a linearized model must be derived so as to apply the linear MPC. The manipulated variables of the process are heat inputs to five vessels shown by Q_1, Q_2, Q_3, Q_4, Q_5. The concentrations of A, B, C, D in each of the five vessels and the temperatures of each of them T_1, T_2, T_3, T_4, T_5 are considered as the states of the process. The controlled outputs are T_1, T_2, T_3, T_4, T_5 plus total destroyed exergy, which is illustrated in Sect. 3.2. The steady-state values indexed by "s" are Q_{1s}, Q_{2s}, Q_{3s}, Q_{4s}, Q_{5s} as the manipulated inputs and T_{1s}, T_{2s}, T_{3s}, T_{4s}, T_{5s} as controlled outputs, and their values are represented in Table 1.

3.2 Exergy Analysis

Keeping in mind the purpose of reduction in the destroyed exergy, the exergy analysis of the described process is conducted in the first step. The concept of exergy analysis for every typical process is intimately illustrated in Sect. 2.1, and it will be applied to the studied process in this section.

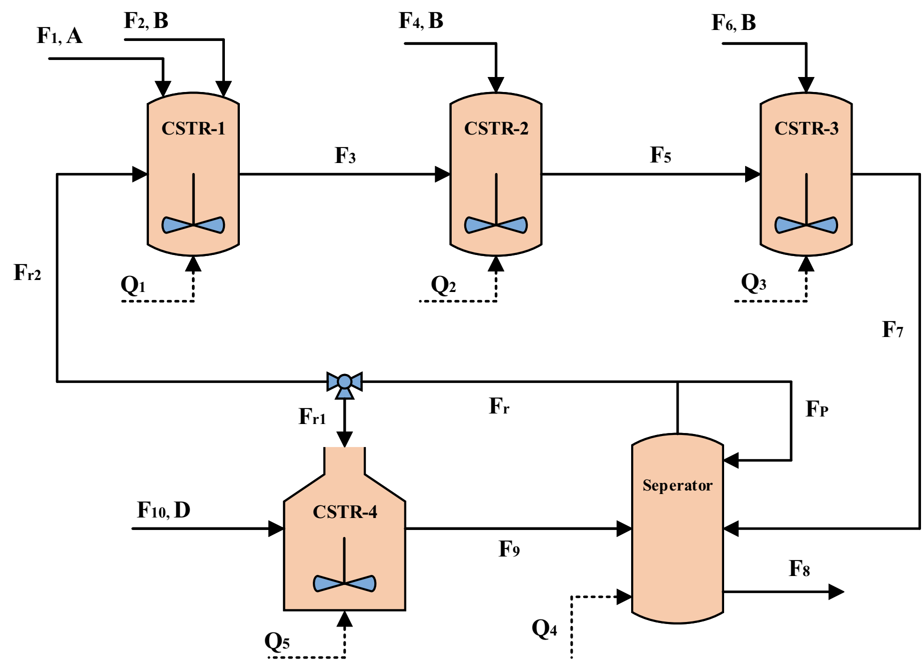

Fig. 1 Flow diagram of alkylation of benzene process

Table 1 Steady-state values for inputs and outputs

Q_{1s}	-4.4×10^6 (J/s)	T_{1s}	477.24 (k)
Q_{2s}	-4.6×10^6 (J/s)	T_{2s}	476.97 (k)
Q_{3s}	-4.7×10^6 (J/s)	T_{3s}	473.47 (k)
Q_{4s}	9.2×10^6 (J/s)	T_{4s}	470.6 (k)
Q_{5s}	5.9×10^6 (J/s)	T_{5s}	478.28 (k)

Destroyed exergy $\left(\dot{X}\right)$ has three significant resources: chemical, physical, and mixing, as mentioned before. These three significant parts will be described for every five vessels (four CSTRs and one flash tank separator) and the exergy destroyed in each vessel through the process will be obtained. The total exergy loss of the process is the summation of five mentioned vessels.

The exergy losses of each vessel could be written as Eq. (5). The work applied to each vessel to obtain mixture $\left(\dot{W}\right)$ is neglected being deficient compared to other terms, whereby the destroyed exergy for CSTR (1) could be written as follows:

$$\dot{X}_{\text{destroyed,total1}} = \sum \dot{X}_{\text{in},1} - \sum \dot{X}_{\text{out},1} + \dot{Q}_1\left(1 - \frac{T_1}{T_0}\right) \tag{11}$$

The chemical exergy of a material stream $\dot{X}_{\text{ch}}$ is directly related to the standard chemical exergy; not only does it remain constant by manipulating the input variables, but also it does not change with time. This means that chemical exergy does not take a role in optimization problem and could be disregarded. From Eq. (4), we have:

$$\dot{X}_{\text{tot}} = \dot{X}_{\text{ph}} + \dot{X}_{\text{mix}} \tag{12}$$

Substituting physical and mixing term of input exergy and output exergy results in:

$$\dot{X}_{\text{in}} = \sum\left(\dot{X}_{\text{ph,in}} + \dot{X}_{\text{mix,in}}\right) \tag{13}$$

$$\dot{X}_{\text{out}} = \sum\left(\dot{X}_{\text{ph,out}} + \dot{X}_{\text{mix,out}}\right) \tag{14}$$

Substituting Eq. (2) and Eq. (3) in Eq. (13) and Eq. (14) ends in:

$$\begin{aligned}\dot{X}_{\text{in}} =& \{[F_1(h_{A1} - h_0) + F_2(h_{B2} - h_0) + F_{r2}(h_{r2} - h_0)] \\ &- T_0[F_1(s_{A1} - s_0) + F_2(s_{B2} - s_0) + F_{r2}(s_{r2} - s_0)]\} \\ &+ \{[F_3 h_{T1} - F_1 h_{A1} - F_2 h_{B2} - F_{r2} h_{r2}] \\ &- T_0[F_3 s_{T1} - F_1 s_{A1} - F_2 s_{B2} - F_{r2} s_{r2}]\}\end{aligned} \tag{15}$$

$$\begin{aligned}\dot{X}_{\text{out}} =& \{[F_3(h_3 - h_0)] - T_0 F_3(s_3 - s_0)\} \\ &+ \{[F_3(h_{T1} - h_3)] - T_0 F_3(s_{T1} - s_3)\}\end{aligned} \tag{16}$$

Air behaves like an ideal gas at pressures less than 200 psi, and the enthalpy difference and the change in entropy are also given by Cangel and Boles (2002):

$$h_2 - h_1 = C_p(T_2 - T_1) \tag{17}$$

$$s_2 - s_1 = C_p \ln\left(\frac{T_2}{T_1}\right) - R \ln\left(\frac{P_2}{P_1}\right) \tag{18}$$

Substitution of Eq. (17) and Eq. (18) in Eq. (15) and Eq. (16) leads to a transparent relation between destroyed exergy in CSTR (1) $\left(\dot{X}_{\text{destroyed,total1}}\right)$, controlled outputs $(T_1, T_2, T_3, T_4, T_5)$ and also manipulated inputs $(Q_1, Q_2, Q_3, Q_4, Q_5)$. The previous procedure for CSTR (1) could be repeated for other vessels. For the sake of simplicity, the destroyed exergy of other vessels is not mentioned here. It worth noting that pressure along the total of the process is assumed to be constant (Ganji et al. 2004), so the pressure term does not take any role in equations. Finally, the total destroyed exergy (TDE) for the process of alkylation of benzene could be calculated by summation of the destroyed exergy of each vessel:

$$\text{TDE} = \sum_{i=1}^{5} \dot{X}_{\text{destroyed,total,i}} \tag{19}$$

Equation (19) plays a primary role in designing of the optimizer as will be shown in the next section.

3.3 Optimizer Design

This section is aimed at designing a novel model predictive control strategy to find a solution through an optimizer to guarantee two main energy-based and control-based objectives: (a) the vessels temperatures follow the set-point values at steady-state condition, (b) Reduce Total Destroyed Exergy (TDE) through the process. Added to two prime goals, MPC is capable of handling control inputs and outputs constraints. Moreover, it must ensure set-point tracking and have a brilliant control performance that can be evaluated by the mean square error of the global system (GMSE). Another advantage of MPC that distinguish it from other control method is applicability for MIMO systems. Implemented for the first time, the TDE obtained from Eq. (13) is considered as a new state along with states mentioned before, indicated by the sixth controlled output in addition to five previous outputs $(T_1, T_2, T_3, T_4, T_5)$. The closer TDE is to zero, the more energy is saved, and more economical is the whole process. The control inputs and outputs for the process have been shown in Fig. 2.

The current controller requires a new cost function, as stated in Eq. (10), in which both energy-oriented objective function (f_1) and control-oriented objective function (f_2) is designed as follows:

$$f_1 = \text{TDE}^2 \tag{20}$$

$$f_2 = \sum_{1}^{H_\text{p}} \left|\left|\hat{y}(k+i|k) - r(k+i|k)\right|\right|_Q^2 + \sum_{0}^{H_\text{u}-1} \left|\left|\Delta\hat{u}(k+i|k)\right|\right|_R^2 \tag{21}$$

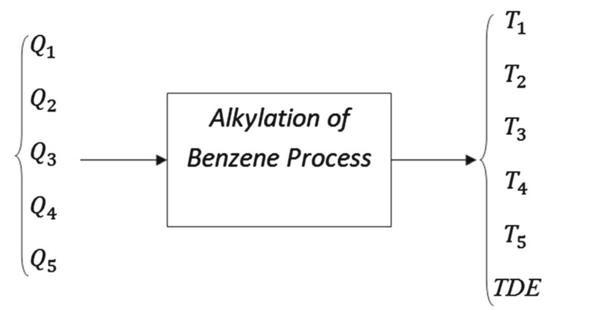

Fig. 2 The manipulated inputs and controlled outputs for the Alkylation of Benzene process

Table 2 Initial values for outputs

T_1	443 (k)
T_2	437.1 (k)
T_3	428.4 (k)
T_4	433.1 (k)
T_5	457.6 (k)

Table 3 MPC controller parameters

H_p	6
H_w	1
H_u	4
Q	$10^6 * \text{diag}([1111111])$
R	$10^{-7} * \text{diag}([11111])$

where Q and R are called weighting matrix, and H_p and H_u are the prediction horizon and control horizon, respectively. Predicted outputs, reference trajectory, and control increments are also shown by $\hat{y}$, r and $\Delta\hat{u}$. The predicted control output matrix $\hat{y}$ and control input matrix is introduced:

$$\hat{y} = [T_1 T_2 T_3 T_4 T_5]^T$$

$$\hat{u} = [Q_1 Q_2 Q_3 Q_4 Q_5 F_4 F_6]^T$$

4 Result and Discussion

The controller desire to steer the system outputs from initial conditions to the steady-state conditions while encountering a disturbance of amplitude 10 in $t = 80$ s. The values of the initial outputs are shown in Table 2. The controller design parameters which were applied in the first simulation are also presented in Table 3. The plant discretization was done using the sampling interval $h = 10$ s, resulting in a discrete-time model ready for applying to the MPC control design.

Referring to the earlier point, it is imperative to meet four main specifications in the new optimizer: to ensure that five outputs temperatures follow to predefined set-points, to reduce total destroyed exergy (TDE) as far as possible, and to handle constraints and to deliver an acceptable control per-

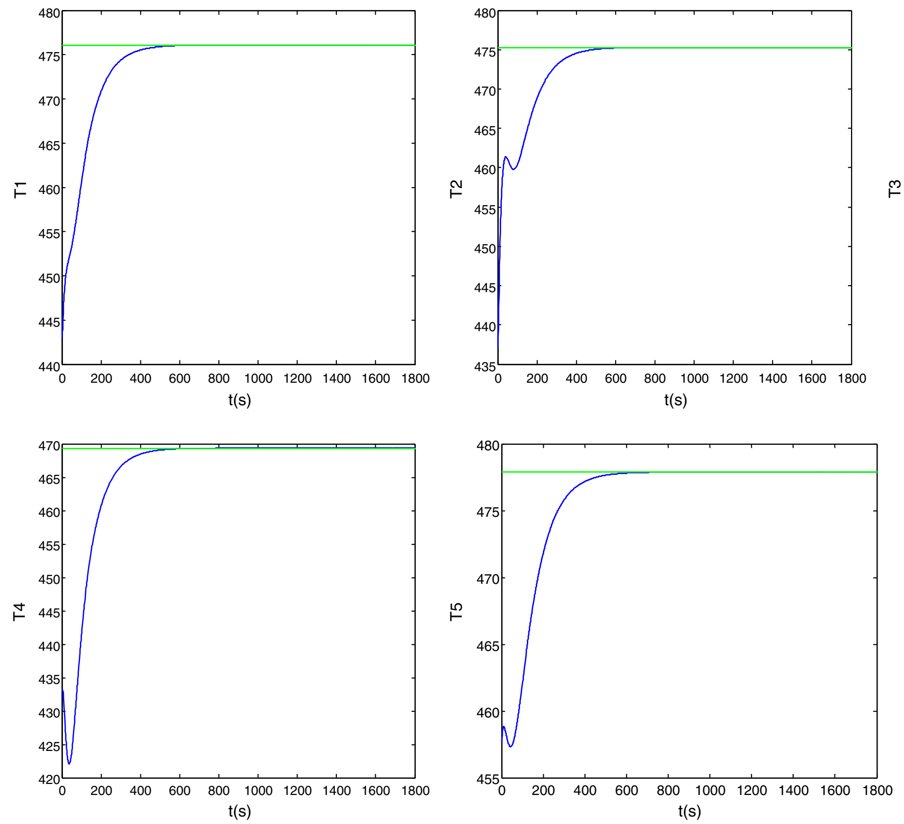

Fig. 3 Set-point tracking of vessels temperatures (T_1, T_2, T_3, T_4, T_5)

formance. The simulation results of the new designed MPC are shown in Fig. 3. As can be seen, five vessels temperatures follow the specific steady-state values from their initial values in the presence of disturbance.

Total destroyed exergy (TDE) is a central feature of the proposed optimizer. The TDE variation with time for various weight ratio $\left(w = \frac{w_1}{w_2}\right)$ is presented in Fig. 4. It is evident from the supplied findings that MPC is capable of decreasing TDE in the presence of disturbance after a while. According to the theory of Thermodynamics, TDE of system or process could not be precisely zero due to the concept of the irreversibility (Van Wylen et al. 1976).

This paper is based on an analysis of two criteria, namely TDE and global mean-square error (GMSE). By calculating these indicators for all cases, the control performance and the amount of energy saved are evaluated. The output weighting matrix $Q \geq 0$ and input weighting matrix $R \geq 0$ as MPC tuning parameters have a profound effect on control performance. These matrixes are assumed to be constant over the prediction horizon $\left(Q = 10^6 * \mathrm{diag}([111111]),\ R = 10^{-7} * \mathrm{diag}([11111])\right)$. According to Table 4, with increasing weight ratio, TDE is reduced, and GMSE is increased. In other words, the amount

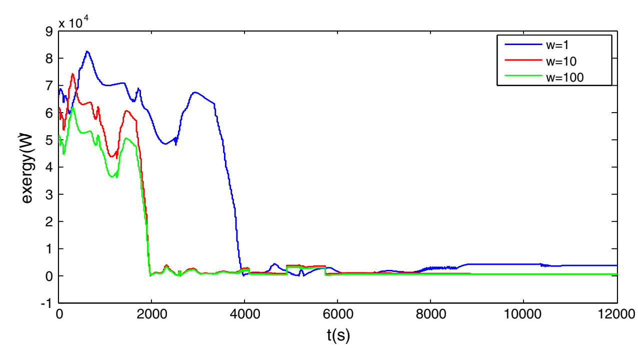

Fig. 4 Total destroyed exergy (TDE) variation for different weight ratio

of energy consumption is decreased in contrast to increased error (not desired controlled from).

Form a general point of view, output weighting matrix Q is appointed to oversee set-point tracking. In further detail, an increase in one of the main diagonals of the Q matrix compel the controller to exceed the corresponding output in importance and minimize deviations in that output. Thus, more substantial output weights would end in outstanding control performance. The effect of Q on TDE reduction is investigated in Fig. 5. As it is clearly shown, TDE experiences a

Table 4 Effect of W on integral of TDE and GMSE

W	Q	R	Integral of TDE (J)	GMSE
1	$0.5 * 10^6 * \text{diag}([111111])$	$10^{-7} * \text{diag}([111111])$	1.35915E+09	0.5276
10	$0.5 * 10^6 * \text{diag}([111111])$	$10^{-7} * \text{diag}([111111])$	2.1095E+08	1.9856
100	$0.5 * 10^6 * \text{diag}([111111])$	$10^{-7} * \text{diag}([111111])$	9.7194E+07	8.3393

Table 5 Effect of Q on Integral of TDE and GMSE

Q	W	R	Integral of TDE (J)	GMSE
$10^6 * \text{diag}([111111])$	1	$10^{-7} * \text{diag}([111111])$	1.3091E+09	0.5197
$10^5 * \text{diag}([111111])$	1	$10^{-7} * \text{diag}([111111])$	1.3604E+09	0.5536
$10^4 * \text{diag}([111111])$	1	$10^{-7} * \text{diag}([111111])$	1.5174E+09	0.5887

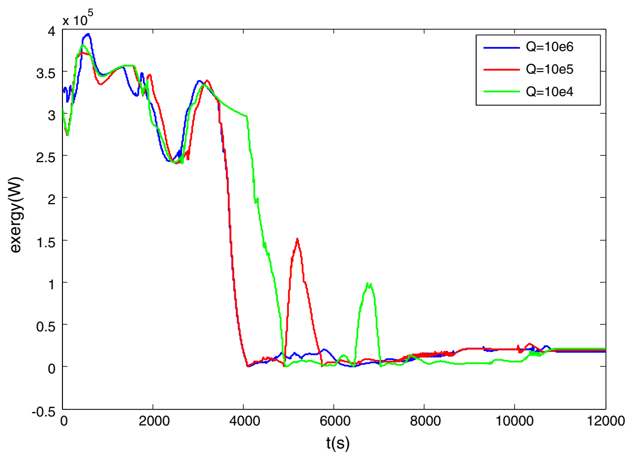

Fig. 5 Total destroyed exergy (TDE) variation for the different magnitude of Q

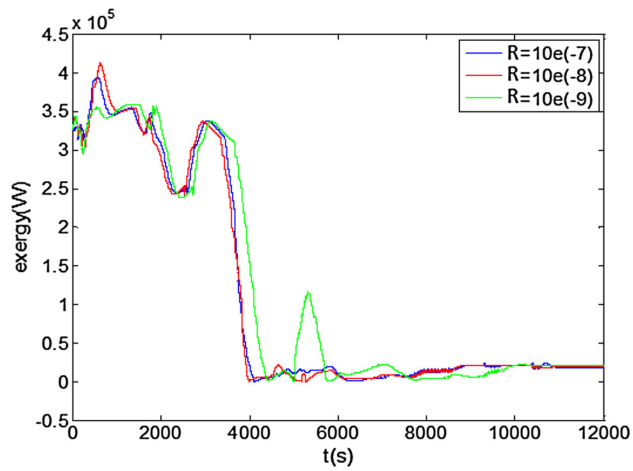

Fig. 6 Total destroyed exergy (TDE) variation for the different magnitude of R

sharp upward trend by decreasing Q and consequently, more energy is saved. Decreasing Q results in less accurate outputs, which stems from GMSE growth, and exacerbate control performance. Rising output weighting matrix, on the other hand, make the MPC regulate vessels temperatures more accurate, while bringing about more destroyed exergy and less saved energy. Turning to Table 5, a careful selection of Q is a high priority to meet the two objectives and tradeoff between energy-saving and control performance.

The input weighting matrix R another tuning parameter in controller design that directly affects control increments. If faster system response is needed, R should be chosen quite small. Conversely, larger R can be chosen if a slower dynamic is acceptable. The effect of R tuning on TDE reduction is investigated in Fig. 6. Looking at Table 6, raising R could lessen GMSE and TDE, which would be the motive for saving more energy. Though lowering R results in faster response, TDE will be increased, i.e., with lowering input weighting matrix, MPC regulates vessels temperatures faster. Apart from improved control performance, which is a positive outcome of increased R, more exergy is destroyed, and less energy is saved. To sum up, a compromise between MPC free parameters, including input and output weighting matrixes is an inevitable part of the proposed strategy that brings a balance between energy and control.

5 Conclusion

A new exergy-based optimization approach has been proposed in an MPC framework for MIMO processes subject to imposed constraints to reduce total destroyed exergy (TDE) and accomplish an optimal control performance in this paper. The established MPC cost function has the characteristics to simultaneously achieve TDE reduction and control regulation in the presence of disturbance. The obtained simulation results indicate the accomplishment of the TDE reduction targeted on energy-saving as well as enhanced control performance, measured by GMSE. Different simulation tests have been conducted to point out how substantial tuning matrixes, denoted by Q and R, direct the outputs regarding control and energy.

Table 6 Effect of R on Integral of TDE

Q	W	R	Integral of exergy (J)	GMSE
$10^6 * \text{diag}([111111])$	1	$10^{-9} * \text{diag}([11111])$	2.2249E+09	0.6242
$10^6 * \text{diag}([111111])$	1	$10^{-8} * \text{diag}([11111])$	1.8321E+09	0.6067
$10^6 * \text{diag}([111111])$	1	$10^{-7} * \text{diag}([11111])$	1.3091E+09	0.5197

Compliance with ethical standards

Conflict of interest Authors have no conflict of interest relevant to this article.

References

Ahmadi, P., Rosen, M. A., & Dincer, I. (2012). Multi-objective exergy-based optimization of a polygeneration energy system using an evolutionary algorithm. *Energy, 46*(1), 21–31.

Aarabi A, Shahbazian, M., & Hadian M. (2015). Improved closed loop performance and control signal using evolutionary algorithms based PID controller. In *Proceedings of the 2015 16th international carpathian control conference (ICCC)* (pp. 1–6). IEEE.

Calli, O., Colpan, C. O., & Gunerhan, H. (2019). Energy, exergy and thermoeconomic analyses of biomass and solar powered organic Rankine cycles. *International Journal of Exergy, 29*(2–4), 172–192.

Cangel, Y., & Boles, M. A. (2002). *Thermodynamics: An engineering approach 4th edition in SI units*. Singapore: McGraw-Hill.

Eboh, F. C., Ahlström, P., & Richards, T. (2016). Estimating the specific chemical exergy of municipal solid waste. *Energy Science and Engineering, 4*(3), 217–231.

Fard, A. N., Shahbazian, M., & Hadian, M. (2016). Adaptive fuzzy controller based on cuckoo optimization algorithm for a distillation column. In *2016 international conference on computational intelligence and applications (ICCIA)*, (pp. 93–97). IEEE.

Ganji, H., Ahari, J. S., Farshi, A., & Kakavand, M. (2004). Modelling and simulation of benzene alkylation process reactors for production of ethylbenzene. *Petroleum and Coal, 46*(1), 55–63.

Gutiérrez, A. S., & Vandecasteele, C. (2011). Exergy-based indicators to evaluate the possibilities to reduce fuel consumption in lime production. *Energy, 36*(5), 2820–2827.

Hadian, M., Aarabi, A., Makvand, A. B., & Mehrshadian, M. (2019a). A new event-based PI controller using evolutionary algorithms. *Journal of Control, Automation and Electrical Systems, 30*(6), 841–849.

Hadian, M., AliAkbari, N., & Karami, M. (2015). Using artificial neural network predictive controller optimized with Cuckoo Algorithm for pressure tracking in gas distribution network. *Journal of Natural Gas Science and Engineering, 27,* 1446–1454.

Hadian, M., Asheri, M., & Salahshoor, K. (2014). A novel exergy-event based model predictive control strategy for energy saving. *Journal of Natural Gas Science and Engineering, 21,* 712–717.

Hadian, M., Mehrshadian, M., Karami, M., & Makvand, A. B. (2019b). Event-based neural network predictive controller application for a distillation column. *Asian Journal of Control, 20,* 987.

Ju, J., Chiu, M.-S., & Tien, C. (2000). Multiple-objective based model predictive control of pulse jet fabric filters. *Chemical Engineering Research and Design, 78*(4), 581–589.

Liu, J., Chen, X., Muñoz de la Peña, D., & Christofides, P. D. (2010). Sequential and iterative architectures for distributed model predictive control of nonlinear process systems. *AIChE Journal, 56*(8), 2137–2149.

Luyao, Z., Cheng, X., Gang, X., Pu, B., & Yongping, Y. (2017). Exergy analysis and economic evaluation of the steam superheat utilization using regenerative turbine in ultra-supercritical power plants under design/off-design conditions. *Energy Science and Engineering, 5*(3), 156–166.

Marty, F., Serra, S., Sochard, S., & Reneaume, J.-M. (2019). Exergy analysis and optimization of a combined heat and power geothermal plant. *Energies, 12*(6), 1175.

Salahshoor, K., & Hadian, M. (2014). A decentralized event-based model predictive controller design method for large-scale systems.

Szargut, J., Morris, D. R., & Steward, F. R. (1987). Exergy analysis of thermal, chemical, and metallurgical processes.

Van Wylen, G. J., Sonntag, R. E., & Borgnakke, C. (1976). *Fundamentals of classical thermodynamics*. New York etc: Wiley.

Wang, Y., & Boyd, S. (2009). Fast model predictive control using online optimization. *IEEE Transactions on Control Systems Technology, 18*(2), 267–278.

Whidborne, J., Liu, G., & Yang, J. (2003) Multiobjective optimization and control.

Wojsznis, W., Mehta, A., Wojsznis, P., Thiele, D., & Blevins, T. (2007). Multi-objective optimization for model predictive control. *ISA Transactions, 46*(3), 351–361.