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Open-loop based controllability criterion applied to stochastic global optimization for intensified distillation sequences

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ABSTRACT

The simultaneous design and control optimization of intensified distillation sequences is a challenging topic that has partially been addressed by doing several simplifications in the process dynamics. This work aims to embed a controllability criterion in a global stochastic optimization algorithm that can solve single objective or multi-objective optimization problems. The proposed optimization algorithm takes the steady state results after solving rigorous tray-by-tray calculations in Aspen Plus®, and sends it to an algorithm written in Matlab® through an interface written in Excel® VBA. It has already been tested to minimize the energy consumption in intensified distillation sequences, but this work is an extension that includes the assessment of the process controllability. By simplifying the process dynamic to only first-order responses, it is possible to assess the controllability of distillation sequences by using only steady state information. The proposed optimization algorithm was applied to three cases of intensified distillation sequences. A comparison between the proposed and the rigorous process dynamics at open-loop was done by using the singular value decomposition (SVD) technique. The results showed that the simplified process dynamics can deal with the optimal design and control of intensified distillation sequences.

1. Introduction

Chemical engineering has been changing and growing together with the society needs to satisfy them through the last century. Before the oil crises in 1970s and the Kyoto protocol in 1997, the primary criterion to design and operate chemical processes was based on economic factors. However, nowadays the challenges in design and operation of chemical processes must satisfy new standards related to the minimization of the consumption of energy sources and the environmental impact derived from pollutants and greenhouse emissions. A thorough search in distillation processes has been urged to meet these new standards since distillation entails by high energy consumption and low thermodynamic efficiency. Heat integration (Gadalla et al., 2005; Haragovics et al., 2012; Iwakabe et al., 2006; Rivera-Ortega et al., 1999) and thermal coupling (Agrawal and Fidkowski, 1999; Dünnebier and Pantelides, 1999; Hernández and Jiménez, 1999) have been the most researched alternatives to effectively reduce the energy demand and greenhouse emissions in distillation in many processes. However, even if the studied processes have attained important energy savings, they might not be economically viable, or difficult to operate reliably.

Due to the existence of several degrees of freedom in intensified distillation processes, its optimal design depends on the selected objective function. Typically, the objective functions comprise the minimization of the Total Annual Cost (TAC), greenhouse emissions,

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eco-indicators, and productivity (Errico et al., 2014; Miranda-Galindo et al., 2014; Quiroz-Ramírez et al., 2017; Sánchez-Ramírez et al., 2016; Vázquez-Ojeda et al., 2013), but none of them has assessed the process controllability as objective function because traditional approaches cannot deal with intensified distillation processes.

The control performance is a crucial issue from an industrial point of view because no matter how economic and sustainable a process might be, it would be impractical if it cannot operate reliably. The controllability of intensified distillation columns has not been thoroughly examined or has been reported only for optimal solutions obtained at steady state (Alcántara-Ávila et al., 2008; Haragovics et al., 2012; Huang et al., 2007; Nakaiwa et al., 1999; Nakaiwa et al., 1998; Ogunnaike and Ray, 1994). Typically, the process dynamics is studied, after a design is optimized at steady state (Acosta-Solórzano et al., 2016; Mansouri et al., 2016), PI or PID controllers are tuned for specific problems; or the worst-case disturbance (μ) criterion is minimized and used for controller evaluation (Muthy Konda et al., 2006; Ricardez-Sandoval et al., 2009). In other optimization studies, the controller has been optimized according to its input variable in a predefined design (Faber et al., 2005; Zheng and Mahajanam, 1999). Finally, some works have embedded the controllability aspects into global optimization approaches such as the work of Zheng and Mahajanam (1999). In their work, a controllability index used theoretical vessels for the inlet and outlet streams of a distillation sequence and evaluated the dynamic response of the outlet streams.

Vega et al. (2014) presented a complete analysis of the design and optimization of chemical processes and pointed out the urging need of creating multi-objective optimization approaches. Also, the inclusion of the control properties as the optimization criterion and the consideration of the controllability during the optimization stage are necessary (Yuan et al., 2012). As mentioned before, most of the works studying the design and controllability of distillation processes have done it separately. Therefore, the simultaneous design and controllability of distillation processes remain as an open research field.

Some of the most recent works that have dealt with the simultaneous optimization of the design and control have proposed a global optimization method that minimizes the TAC and the condition number at zero frequency (i.e., steady state), which as the used controllability criterion (Vázquez-Castillo et al. 2015; Contreras-Zarazúa et al. 2016). Nevertheless, the use of the condition number at frequency zero is insufficient to predict properly physical dynamic behavior in many cases (Morari and Zafiriou, 1989), and especially in intensified distillation processes.

2. Proposed controllability criterion (A_γ)

Optimization problems can be solved in a deterministic way or in a stochastic way (González, 2007). The former implies a clear understanding of the mathematical model to manipulate the process variables to find an optimal value. The latter can perform the process optimization without an explicit model, a specific expression of the objective function regarding of defined variables suffices. Therefore, the stochastic optimization can be advantageous to solve optimization problems that use process simulations. Therefore, it is possible to execute optimizations by using rigorous models in process simulators without any major difficulties.

As mentioned before, it is possible to implement stochastic algorithms relatively easily and to couple them with commercial simulation software (e.g., Aspen Plus®). Thus, optimization problems that implicitly embed rigorous tray-by-tray models, thermodynamic relations, and kinetic models for reactions in the simulation software. From the optimization viewpoint, the inclusion of a controllability criterion increases the complexity of the solution strategy because two main reasons:

1. The dynamic model must be defined explicitly to optimize it (deterministic approach).
2. Extensive and tedious manual calculations in the simulation software are necessary (trial-and-error approach).

The previous situations lead to the following question: Is it possible to obtain reliable information about the dynamic behavior of a system from only steady state information? This work attempts to answer the previous question by proposing a global stochastic optimization method that embeds a controllability criterion.

The addition of dynamic simulations in a global optimization framework will increase its complexity and computation time. To avoid this issue, it is better to replace rigorous dynamic simulations with approximated calculations at steady state, and to add the latter in the global stochastic optimization.

Skogestad and Morari (1987) have proved that it is possible to assess the dynamic properties of conventional distillation columns from only steady state information. Their derived general model was simplified and applied to the separation of binary mixtures under the following assumptions: (1) the flow dynamics are immediate, and (2) all trays have the same dynamic responses. The work of Zheng and Mahajanam (1999) used the assumptions above to assess controllability of conventional distillation columns also. In this work, the derived general model derived by Skogestad and Morari (1987) is not simplified to binary mixtures, but extended to intensified distillation sequences involving the separation of multicomponent mixtures.

Knowing the process dynamics at open-loop is not enough to evaluate its controllability. Therefore, a mathematical analysis is necessary. Klema and Laub (1980) proposed the use of the singular value decomposition (SVD) technique in the assessment of theoretical control properties. The condition number (γ) and the minimum singular value (σ_*) give valuable information about the theoretical control properties for a chosen frequency range of a transfer function matrix for a multivariable system. The condition number is the ratio of the maximum and minimum singular value, and it represents the sensitivity of the system to input uncertainty. Large values of γ must be avoided because they imply that the system is ill-conditioned. The minimum singular value represents the system invertibility, and values close to zero must also be avoided. Therefore, values of γ close to one and large values of σ_* are desired. It is necessary to obtain the process matrix transfer functions to apply the SVD.

In a previous work, Cabrera-Ruiz et al. (2011) showed that there is a narrow solution space for the optimization of intensified distillation sequences. Therefore, it is crucial to adequately select the objective function that can be readily evaluated from the optimization variables so as to reduce the computation time in finding optimal solutions. Since the inclusion of rigorous dynamic simulations into a global optimization will increase the framework complexity and the computation time, it is better to replace rigorous dynamic simulations by approximated calculations at steady state, and to add the latter in the global stochastic optimization.

Skogestad and Morari (1987) have effectively demonstrated the usefulness of their proposed approach to calculate the time constant in a binary distillation column. However, their approach remains unaddressed for intensified distillation sequences. Therefore, this work aims to propose a controllability criterion that also uses an approximated time constant

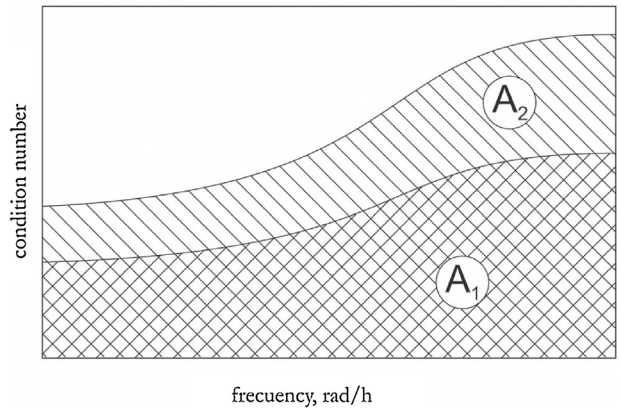

Fig. 1 – Conceptual representation of the area under the curve for the condition number of two hypothetic distillation structures.

(τ) and assumes that all responses in the column are first order. τ can be obtained by perturbing the steady state as follows:

$$\tau = \frac{\sum_{i=1}^{N+1} M_{if}\,\Delta x_i}{\Delta S_i} \quad (1)$$

$$\Delta S_i \overset{def}{=} D_f\,\Delta y_D + B_f\,\Delta x_B \quad (2)$$

where ΔS_i is the supply imbalance (i.e., the composition change at the column top and bottom), M_{if} is the holdup inside de column for each stage i, Δx_i is the change in the liquid composition of any component on stage i. D_f is distillation rate, Δy_D is the composition change in the distillate, B_f is the bottom rate, and Δx_B is the composition change in the bottoms. The calculation of the time constant will allow the construction of the transfer function matrix and consequently the assessment of the singular values in a frequency other than zero.

All the data to solve Eqs. (1) and (2) can readily be obtained from Aspen Plus® regardless the number of components in a mixture. Also, the manipulated variables were perturbed 0.5% to calculate the transfer function matrix. Thus, it is possible to perform a control analysis at open loop. The pressure drop assumed for each stage depends according to the nature of the studied structure to get more reliable information in the steady state. In this work, a heuristic pressure drop of 0.69 kPa per stage was assumed.

Once the assumed first-order transfer functions are calculated, the SVD is executed. However, the criterion to determine if a solution has "*worse*" or "*better*" controllability has been defined qualitatively by comparing γ and σ_* for all the alternative distillation candidates in the previous works (Alcántara-Ávila et al., 2008; Tamayo-Galván et al., 2008). Therefore, it is necessary to quantitatively define a criterion of how "*good*" or "*bad*" the controllability of a solution is in terms of γ and σ_*. The condition number was selected as the only controllability criterion because it implicitly includes the minimum singular value. Since close values to one are desired for the condition number, it can be inferred that the best solution will have the minimum area below the condition number in the frequency domain.

Fig. 1 shows the condition number areas A_1 and A_2 corresponding to two theoretical solutions. The area A_1 is less than the area A_2, and as a consequence the controllability of the distillation structure represented by A_1 can be better than A_2. Thus, the minimization of the area of the condition number can be used as the controllability index.

Only low values of the frequency range (i.e., $0 < \omega \leq 100\,\text{rad}\,\text{h}^{-1}$) were considered for the sake of fair comparison because high frequency values lack of realistic physical sense (Morari and Zafiriou, 1989).

3. Case study

A comparison between the proposed simplified model and the rigorous model was done to validate the reliability of the proposed simplified model in assessing the controllability of

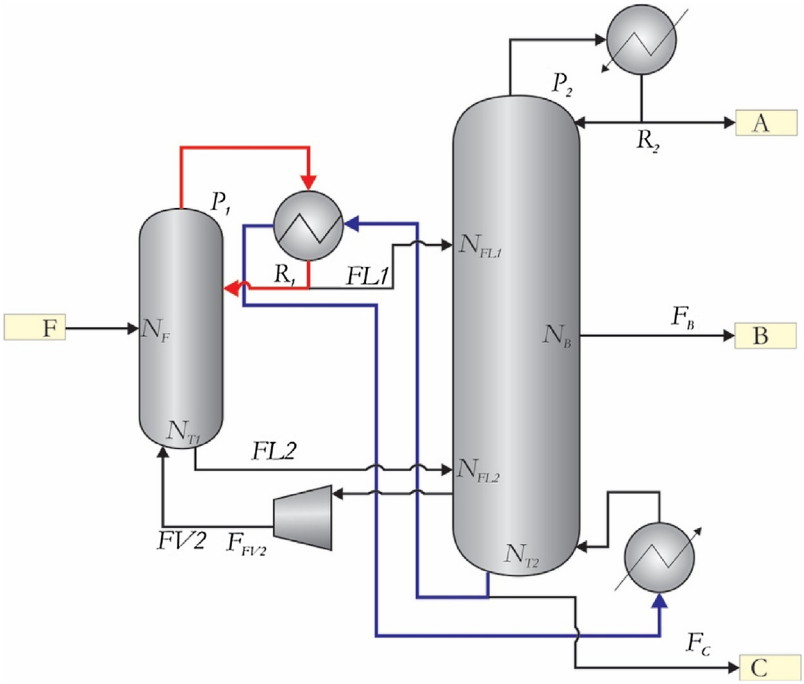

Fig. 2 – HIVC scheme and their optimization variables.

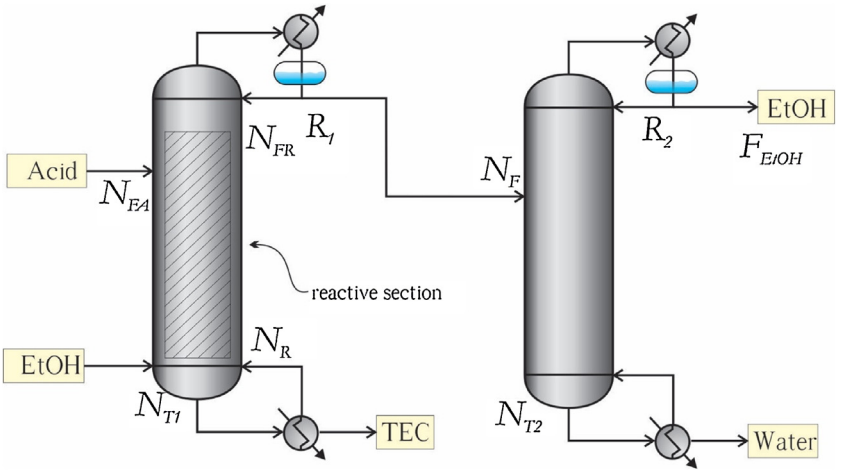

Fig. 3 – CSR scheme and their optimization variables.

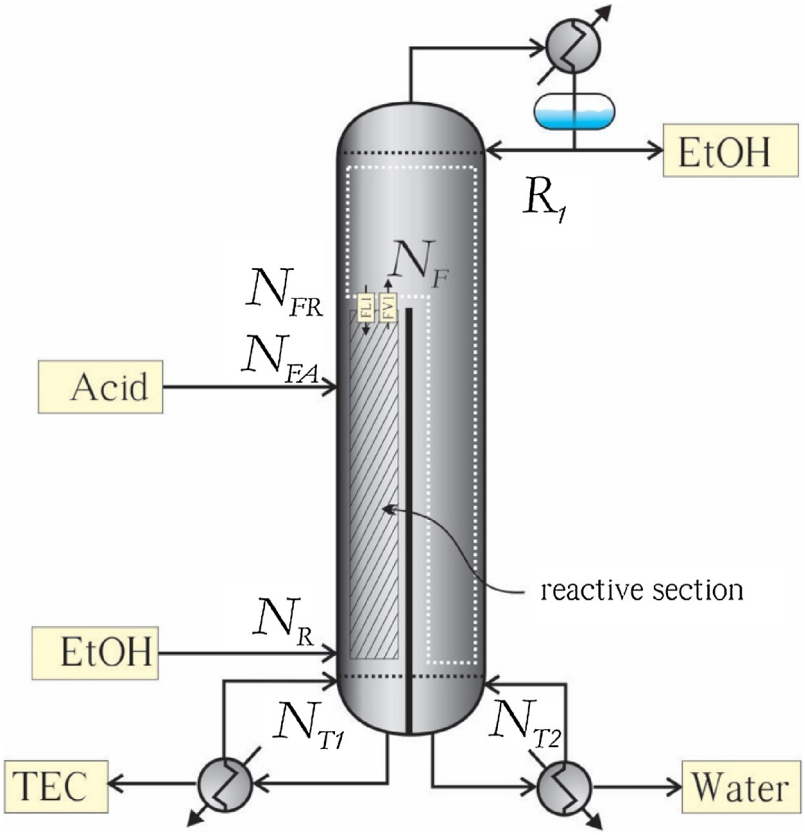

Fig. 4 – RDWC scheme and their optimization variables.

intensified distillation sequences. For such purpose, three case studies were analyzed:

1. A distillation structure with heat integration and vapor recompression (HIVC) in Fig. 2.
2. A conventional reactive distillation sequence (CSR) in Fig. 3.
3. A dividing wall reactive distillation column (RDWC) in Fig. 4.

Case 1 uses a previously reported feasible solution obtained after solving a multi-objective optimization problem (Alcántara-Ávila et al., 2012) for HIVR as the initial design. Cases 2 and 3 assess the triethyl citrate (TEC) production from ethanol (EtOH) and citric acid (Acid) (Santaella et al., 2014). They use the reaction models reported by Kolah et al. (2007, 2008). Also, the chosen designs of CSR and RDWC correspond to the Pareto-optimal designs obtained after solving a multi-objective optimization problem.

The reported solution in each case was taken as the initial design in the stochastic global optimization; then several Pareto optimal designs were chosen randomly with different values of the condition number area in such a way that the area continuously decreases.

In case of a multi-objective optimization problem, Fig. 5 shows how several optimal designs (A–F) are taken randomly from a hypothetic Pareto front that minimizes the proposed controllability criterion (i.e., area of γ) and a given objective function $f_1(\mathbf{x})$ (e.g., cost, CO_2 emissions, energy consumption). In case of a single optimization problem, several local optimal designs are taken from a random number of iterations. Different values of optimization variables (e.g., temperature, pressure, internal flows, stages) exist among the designs in

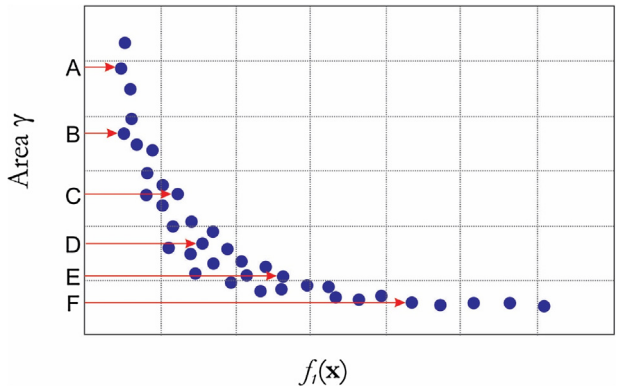

Fig. 5 – Conceptual representation for the selection of several designs along a hypothetical Pareto front.

such a way that the area of γ gradually decreases as follows: $A_{\gamma A} > A_{\gamma B} > A_{\gamma C} > A_{\gamma D} > A_{\gamma E} > A_{\gamma F}$. The key point in this approach is that although the simplified solution is not equal or close to the rigorous solution, a tendency in the evolution of the minimization direction of the condition number area is attained. In other words, the key point is that the optimal solution by the simplified model coincides with the optimal solution of the rigorous model.

To demonstrate the effectiveness of the reduced model, the generation of two random structures with different values in the condition number area will suffice. However, the proposed controllability criterion in this work uses stochastic algorithms to find optimal solutions through a framework that combines Aspen Plus® -Excel® -Matlab® as described in the following section.

4. Optimization

Stochastic algorithms were implemented through an interface that links Aspen Plus®, Excel®, and Matlab® (Cabrera-Ruiz et al., 2011). Rigorous simulations are done at steady state in Aspen Plus; the stochastic algorithm is programmed in Excel® VBA and it also stores the steady state and SVD data. Additionally, the SVD is done in Matlab®. For the sake of clarity, Fig. 6 shows how the controllability index (i.e., A_γ) is embedded in the stochastic global optimization software framework. It can be seen that all the design variables can be manipulated (e.g., the variables on the right side of Eq. (3)). The numbers in circles denote the order in which the optimization framework is executed.

The HIVC was optimized by using a Simulated Annealing Technique (Cabrera-Ruiz et al., 2012) where A_γ in Eq. (3) is the single objective function. For CSR and RDWC the hybrid optimization algorithm that combines Differential Evolution with Tabu List (DETL) developed by Srinivas & Rangaiah (2007) was used. In these latter cases, a bi-objective function that minimizes the TAC and A_γ. Eqs. (4) and (5) show the objective functions for CSR and RDWC, respectively. The TAC calculations were done according to the Guthrie Method reported in Turton et al. (2004). Three years of payback time for equipment and catalyst cost and a total production of 10,000 metric tons per year were assumed. The DETL algorithm was program in Excel® (Sharma et al., 2012). The algorithm to calculate A_γ and to evaluate the SVD was written in Matlab®.

$$Min\,(A_\gamma) = f\,(R_1, R_2, F_B, F_C, F_{FV2}, N_{T1}, N_{T2}, N_{F1}, N_{FL1}, N_{FL2}, N_B, P_1, P_2,) \quad (3)$$

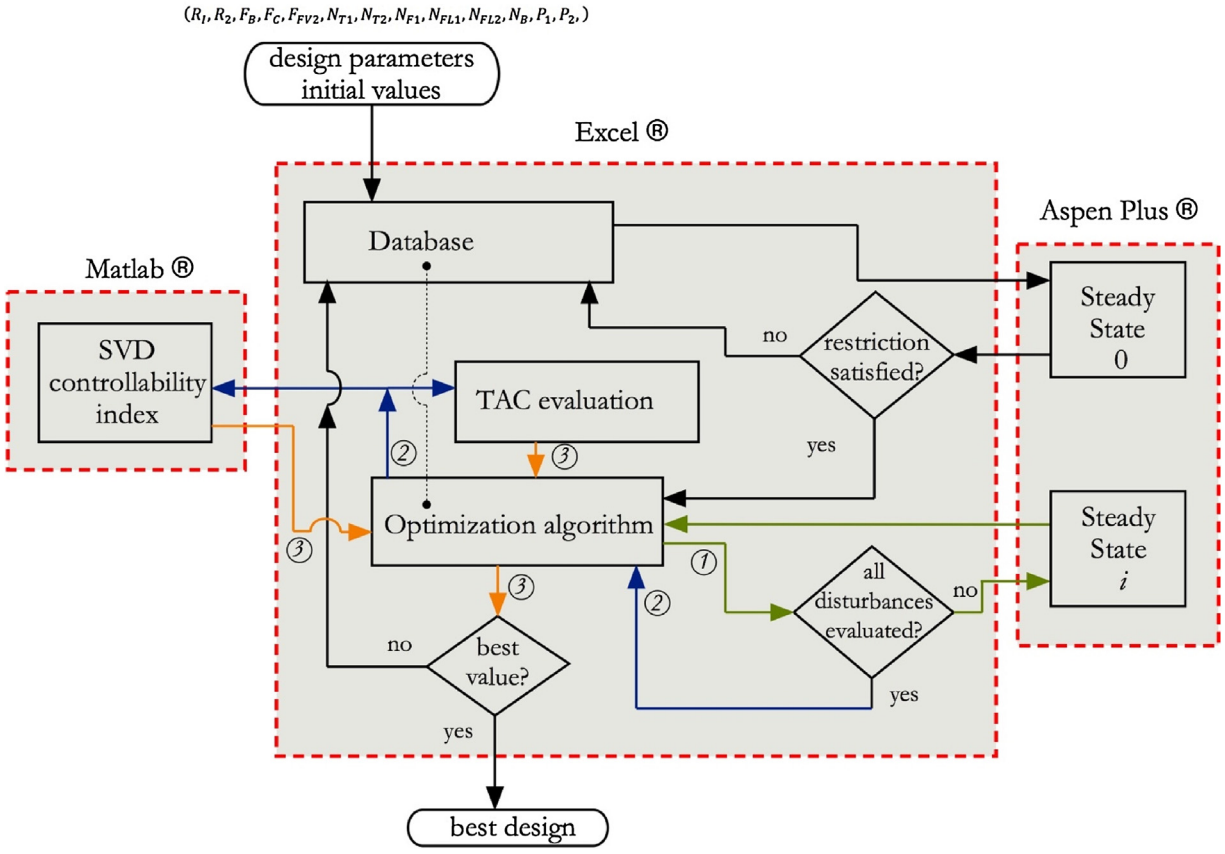

Fig. 6 – Flowsheet with the optimization algorithm embedded in the software framework.

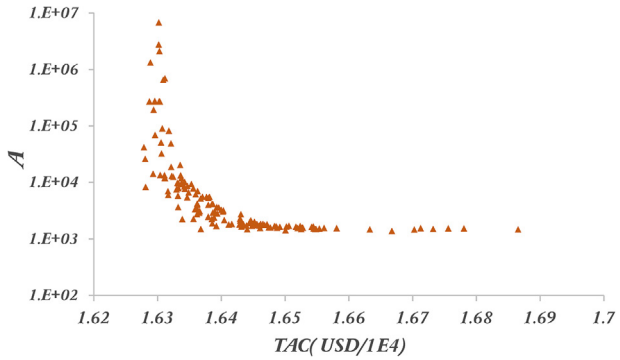

Fig. 7 – Pareto front solution for the CSR sequence.

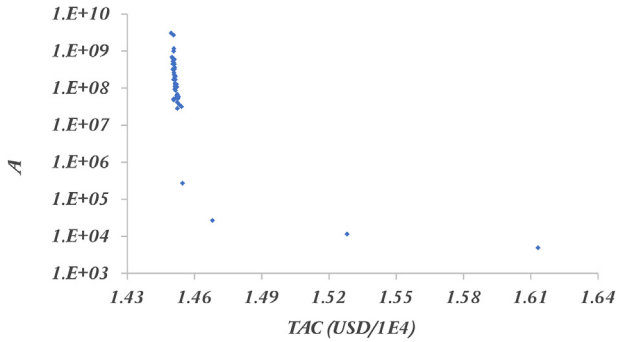

Fig. 8 – Pareto front solution for the RCDW sequence.

$$Min\,(A_\gamma, TAC) = f\,(R_1, R_2, F_A, F_T, F_E, N_{T1}, N_{FA}, N_{FE}, N_{FR}, N_R, Q_1, Q_2) \quad (4)$$

$$Min\,(A_\gamma, TAC) = f\,(R, F_A, F_T, F_E, F_L, N_{T1}, N_{FA}, N_{FE}, N_{FR}, N_R, Q_1, Q_2) \quad (5)$$

The objective functions in Eq. (3) through Eq. (5) are constrained in all cases by the following equation

$$\vec{y}_m \geq \vec{x}_m \quad (6)$$

where $\vec{y}_m$ is the calculated purity for each component m and $\vec{x}_m$ is the assigned purity target.

5. Results and discussions

Figs. 7 and 8 show the obtained Pareto-front for the multi-objective optimization problem in cases 2 and 3. The selected designs, as mentioned before, were chosen randomly. Tables 1–3 show the values of the optimization variables for different designs in the cases in Section 3. It is important to notice how the process structure influences on the optimization variables. For example, in Table 1 (HIVC case) it can be observed that the stage number is very similar in both results. However, other variables have larger differences, for example, the pressure. Then it is clear how certain variables have more influence into the optimization, and these variables can also influence the dynamic behavior. On the other hand, Tables 2 and 3 for the reactive distillation cases the stages number plays an important role. Therefore, some optimization variables have an impact stronger in finding the optimal solution.

Table 1 – Designs A and B for HIVC.

Variable	Design A	Design B
R_1[−]	1.34	0.68
R_2[−]	8.26	6.3
F_B [kmol/h]	63.15	62.64
F_C [kmol/h]	25.53	26.74
F_{FV2} [kmol/h]	97.08	91.05
N_{T1}[−]	12	12
N_{T2}[−]	35	35
N_F[−]	11	11
N_{FL1}[−]	10	11
N_{FL2}[−]	17	24
N_B[−]	23	20
P_1 [atm]	7.20	6.35
P_2 [atm]	4.07	1.63

Table 2 – Designs A and B for CSR.

Variable	Design A	Design B
R_1[−]	0.03	0.02
R_2[−]	1.02	0.72
F_{EtOH} [kmol/h]	35.93	40.22
N_{T1}[−]	61	61
N_{T2}[−]	35	20
N_{FR}[−]	6	5
N_R[−]	55	56
N_{FA}[−]	6	9
N_F[−]	7	3

Table 3 – Designs A and B for RDWC.

Variable	Design A	Design B
R_1[−]	1.45	2.58
FL1 [kmol/h]	1.04	1.16
N_{T1}[−]	67	99
N_{T2}[−]	12	17
N_{FR}[−]	3	1
N_{FA}[−]	4	2
N_R[−]	67	95

Eq. (7) shows the transfer function matrix obtained from the rigorous model at open loop for design B in HIVC (Table 1). Similarly, Eq. (8) shows the transfer function matrix obtained from the simplified model at the open loop.

$$\begin{array}{c|ccc} & R_2 & F_B & F_C \\ x_A & \frac{6.5344}{1+0.1252s} & \frac{-0.0664}{1+0.2670s} & \frac{0.0124}{1+0.1327s} \\ x_B & \frac{5.4700}{1+0.2763s} & \frac{-1.4844}{1+0.2869s} & \frac{0.0132}{1+0.2961s} \\ x_C & \frac{-0.1892}{1+0.2658s} & \frac{0.0484}{1+0.2409s} & \frac{-0.0024}{1+11.4690s} \end{array} \quad (7)$$

$$\begin{array}{c|ccc} & R_2 & F_B & F_C \\ x_A & \frac{0.0189}{1+5.2158s} & \frac{1.9159}{1+0.5112s} & \frac{0.7513}{1+0.5413s} \\ x_B & \frac{0.0120}{1+5.2158s} & \frac{0.2780}{1+0.5112s} & \frac{0.7604}{1+0.5413s} \\ x_C & \frac{0.0078}{1+5.2158s} & \frac{-0.0266}{1+0.5112s} & \frac{-0.0321}{1+0.5413s} \end{array} \quad (8)$$

where x_A, x_B, and x_C are the liquid molar fractions of streams A, B, and C, respectively.

Figs. 9–12 show the minimum singular and the condition number values for the proposed approximated approach

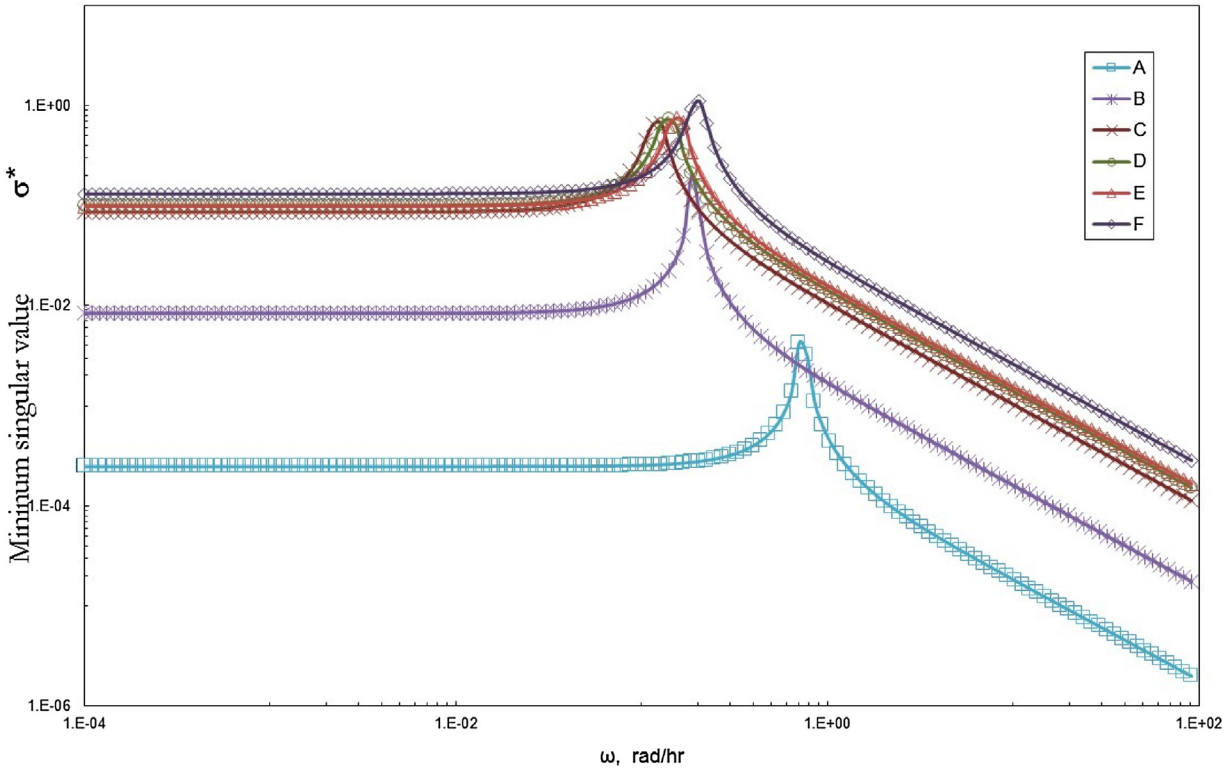

Fig. 9 – Minimum Singular Value for HIVC by the proposed simplified approach.

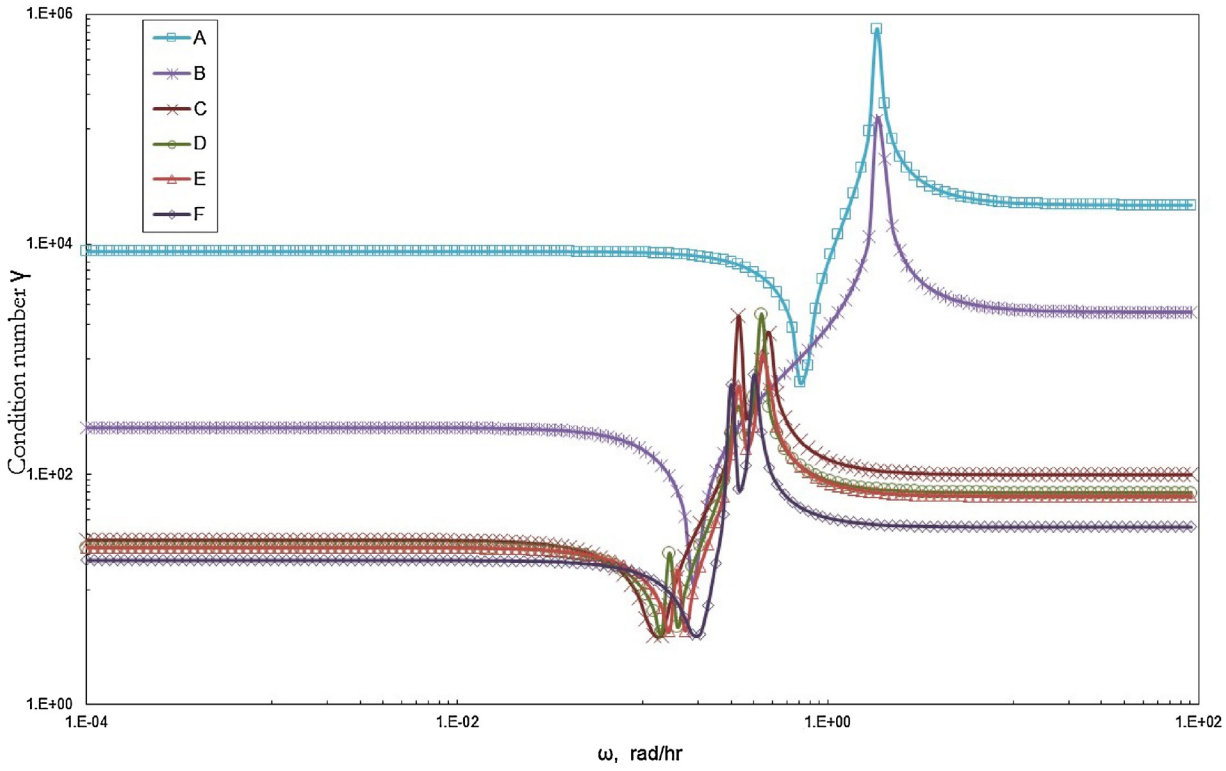

Fig. 10 – Condition Number for HIVC by the proposed simplified approach.

and the rigorous approach for the HIVC sequence. Although the SVD results in the simplified approach and the rigorous approach are not identical, both move towards the minimization of Eq. (3). Also, the values of A_γ in each approach are separated by one order of magnitude, however there is a good agreement between both approaches in obtaining the best design with a minimum A_γ.

Fig. 13 shows more clearly the relation between A_γ for the simplified and rigorous approaches. There are smaller deviations in A_γ for the worst taken solution (Design A) and larger deviations for the best taken solution (Design F). In the proposed approach, the value of A_γ steadily decreases, therefore a better design in terms of controllability is obtained after each iteration.

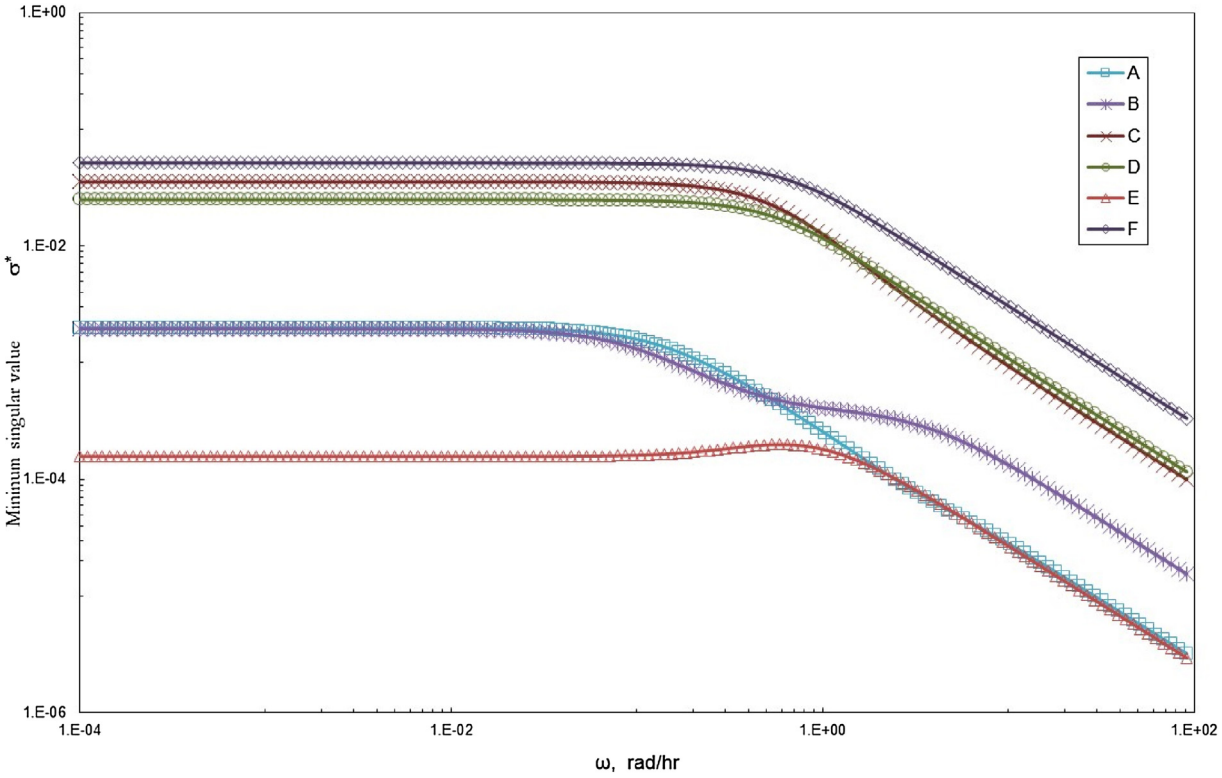

Fig. 11 – Minimum Singular Value for HIVC by the rigorous approach.

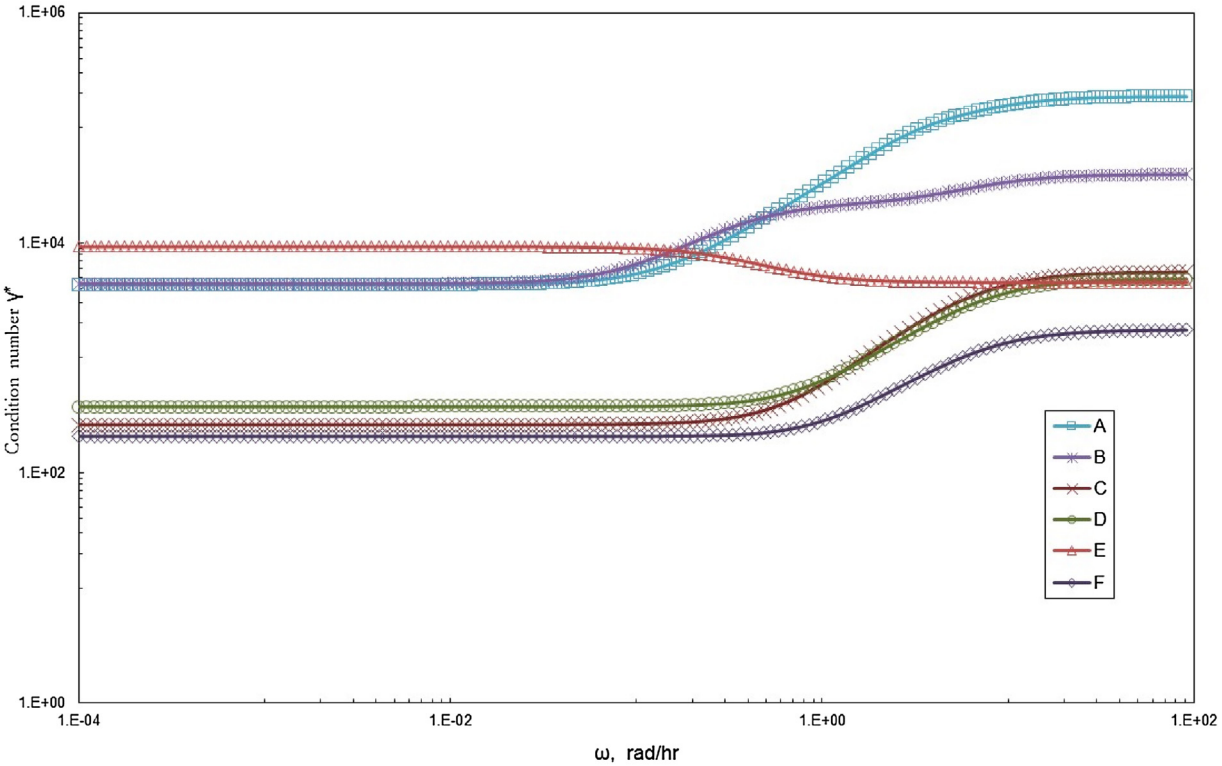

Fig. 12 – Condition Number for HIVC by the rigorous approach.

For the multi-objective optimization of CSR and RWDC, the controllability assessment between the simplified and the rigorous approaches is more challenging due to the intrinsic reactive system in the optimization problem. Figs. 14–17 show the minimum singular and the condition number values for the simplified approach and the rigorous approach for the CSR sequence. Similarly, the solutions A to F denote several designs from the Pareto-optimal solutions. Also, there is a tendency towards the minimization of Eq. (4).

Fig. 18 shows more clearly the relation between A_γ for the simplified and rigorous approaches. Similarly, there are smaller deviations in A_γ for the worst taken solution (Design A) and larger deviations for the best taken solution (Design F). In both approaches, the value of A_γ steadily decreases. Therefore,

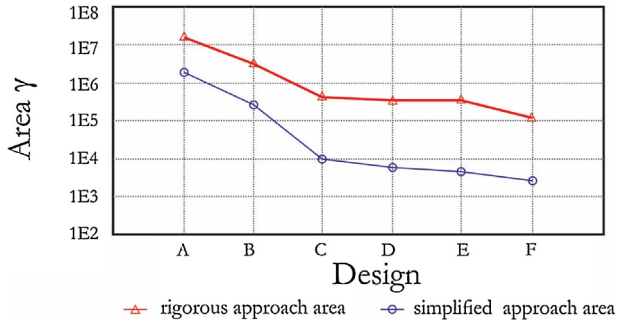

Fig. 13 – Evolution trajectory in minimization of A_γ at several random designs for HIVC.

better designs in terms of controllability are obtained despite of the TAC worsening.

The difference between $A_{\gamma C}$ and $A_{\gamma D}$ in Fig. 18 is very small for the simplified approach, therefore, a more detailed analysis near these designs was done to investigate if Design D is actually better than Design C or if these results come from the simplifications in the proposed approach.

It is necessary to take some cautions in interpreting the value of A_γ because it cannot be concluded if C is actually better than D due to the simplification in the area calculations. Fig. 19 shows four designs namely A', B', C' and D' which were also randomly calculated between the designs C and D of the simplified model for the case CSR in Fig. 18. The results in Fig. 19 imply that because of the vicinity in the designs C and D and the differences in order of magnitude by the proposed and reduced models, these little differences in the design will not be significant in the final solution because stochastic algorithms can also take solutions not optimal or even infeasible during the iteration steps. To avoid choosing designs with similar values of the area, a constraint to limit the sensitivity level for the area can be assigned to the algorithm (e.g., avoid area with small differences, in these work cases this difference was set arbitrarily at 125). Based on the previous statement, when the design variables are very close there can be deviations towards the direction of controllability improvement.

Similarly, Figs. 20–23 show the minimum singular and the condition number value of the proposed model and the rigorous model for the RDWC at several random designs. In Figs. 18 and 24, it can be observed that there is a similar evolution trend in finding better dynamic performance after each iteration for the simplified and rigorous approaches.

Although there are designs with similar values of their optimization variables, their condition numbers can remarkably differ between them. Nevertheless, the design with the best condition number is not far from the actual design with the best open-loop performance in rigorous approach. In the worst case scenario, a good design close to the optimal dynamic performance behavior can be found.

From the three studied cases, it can be noticed that the best matching tendency corresponds to the HIVIC and RDWC cases, and the worst for the CRS. From the obtained optimal solutions, it can be considered that the presented approach works better for the intensified cases. This is not trivial because when recycle streams exist in the sequence, the internal liquid and vapor flows increase. When the inner flows increases, the value of the time constant associated with the column stages

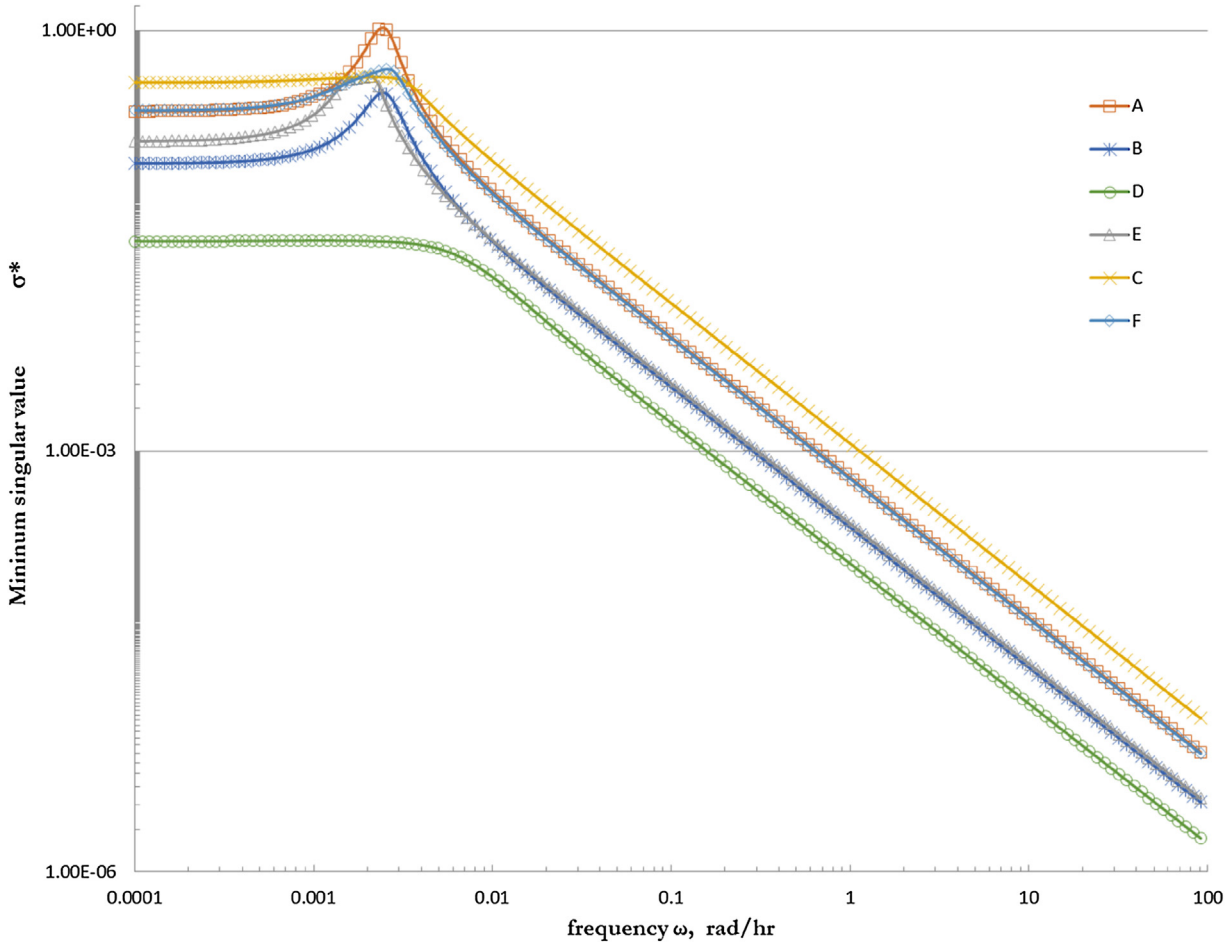

Fig. 14 – Minimum Singular Value for CSR by the proposed simplified approach.

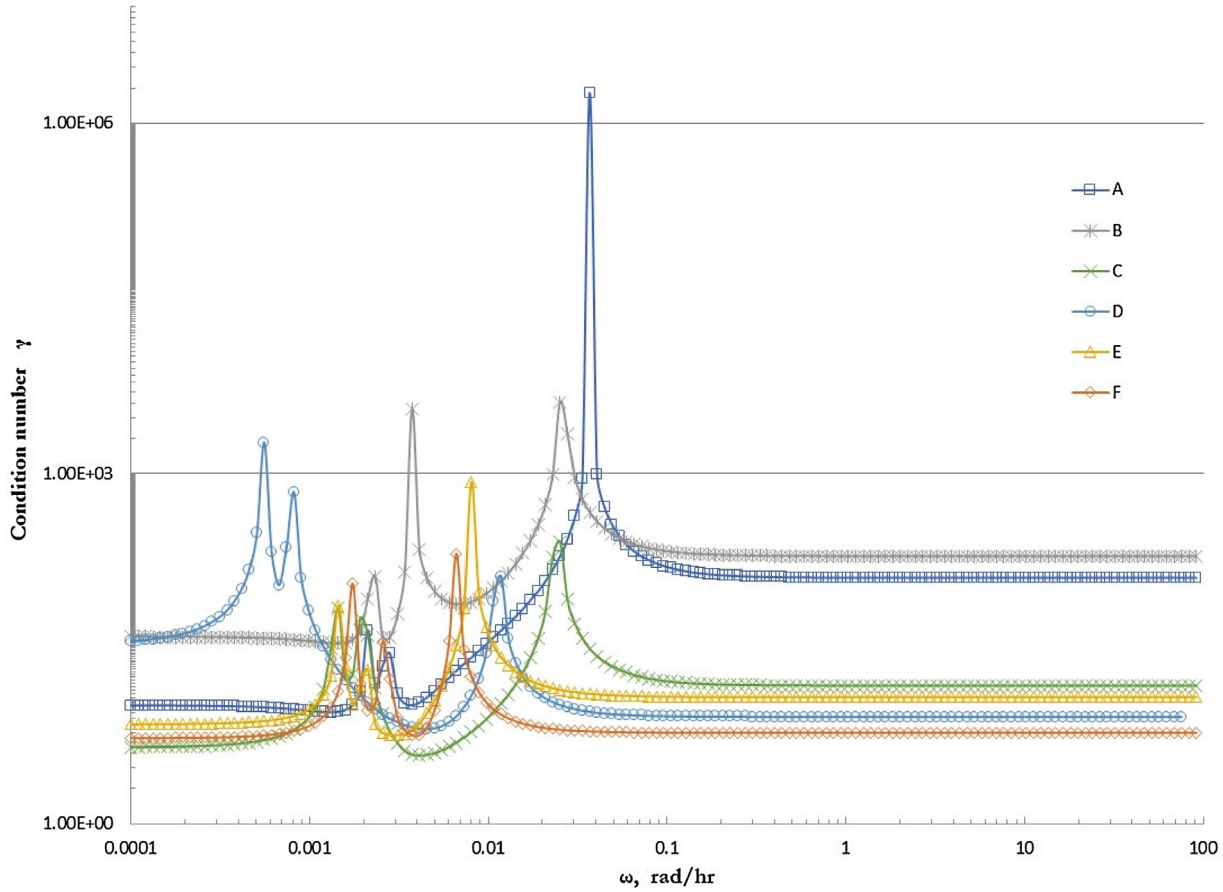

Fig. 15 – Condition Number for CSR by the proposed simplified approach.

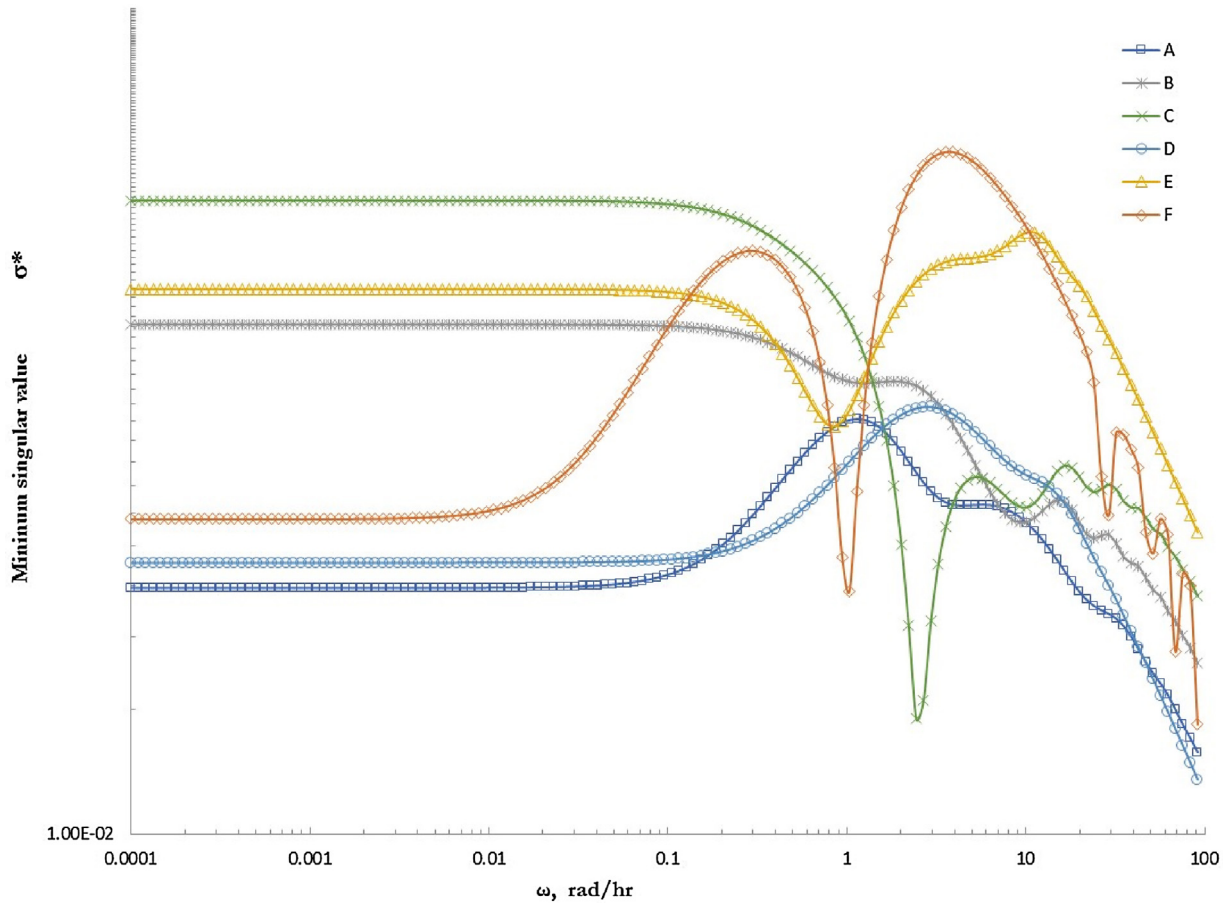

Fig. 16 – Minimum Singular Value for CSR by the rigorous approach.

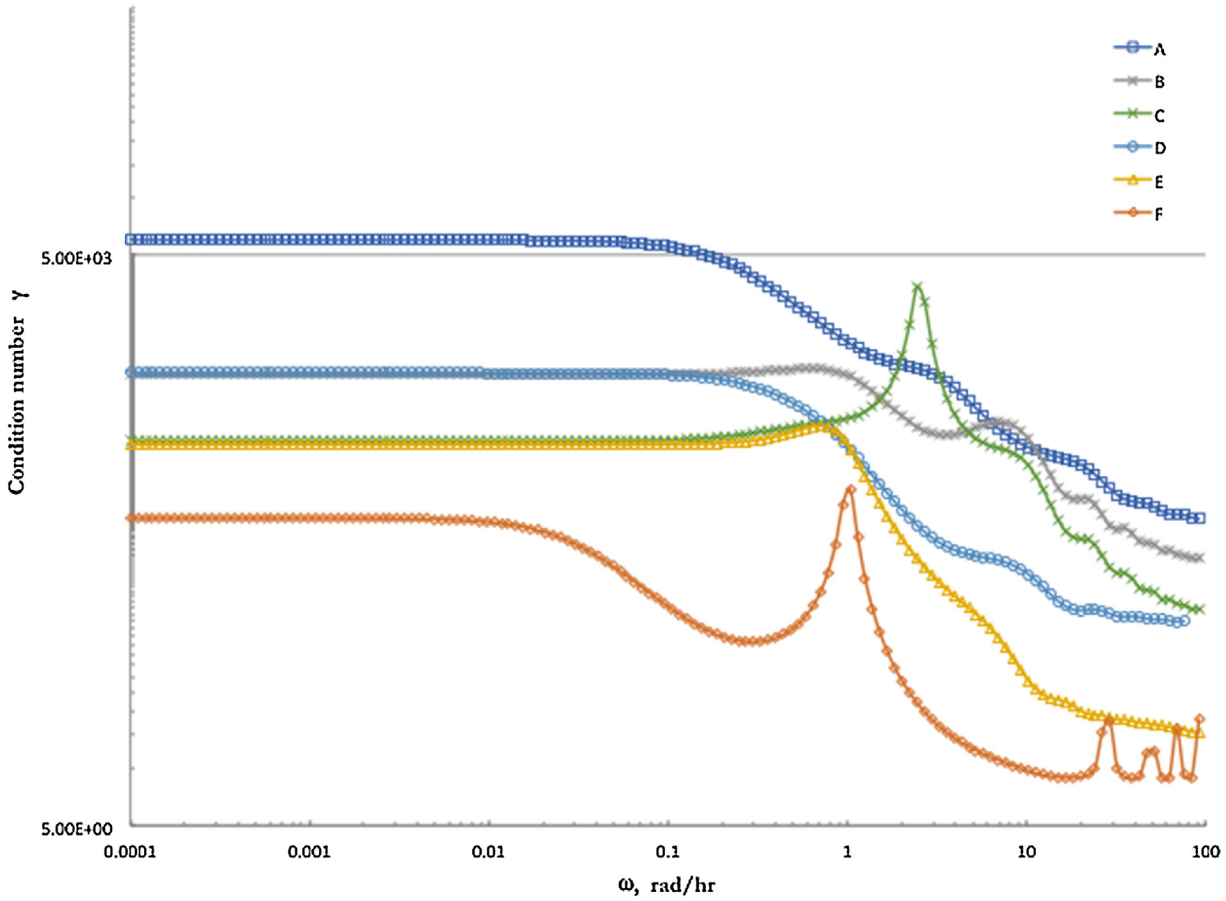

Fig. 17 – Condition Number for CSR by the rigorous approach.

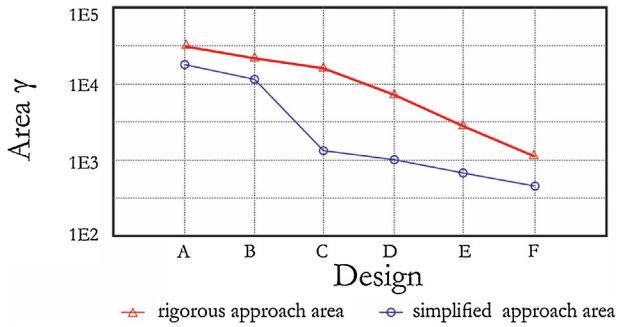

Fig. 18 – Evolution trajectory in the area minimization at several random designs for case CSR.

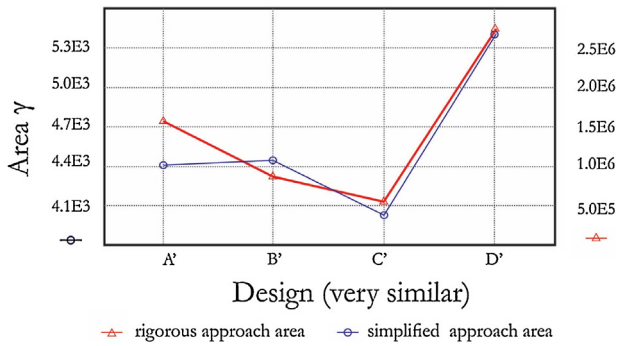

Fig. 19 – Evolution trajectory in the area minimization at several similar designs for case CSR.

became greater that the remaining equipment (condenser and reboiler, which can be neglected); then the assessment of the time constant from steady state becomes valid.

6. Conclusions

A new strategy was proposed to consider the controllability as optimization criterion along with the optimal design at steady state. It was observed that the proposed approach can suffice and can effectively find global stochastic optimal solutions. The first order simplifications in the dynamic responses were a good approximation in most of the cases because the dynamic responses in the rigorous model were not very far from first order responses. The adopted assumptions by the proposed approach are valid to analyze the controllability of complex distillation configurations and to find optimal designs regarding their dynamic performance. For all cases, the area obtained by the simplified approach always gave values lower than the rigorous approach. Thus the simplified method can be regarded as a lower bound for open-loop stability, which is valid since simple first order responses are assumed.

The new objective function based on the minimization of the area under the curve for the condition number after calculating the SVD for the complex distillation structures proved to be efficient to find designs with good controllability. This approach can also be implemented in multi-objective optimization algorithms because only steady state information is necessary. Also, since the controller must ensure that the closed-loop system is stable, regardless of the open-loop stability, the close-loop analysis must be done.

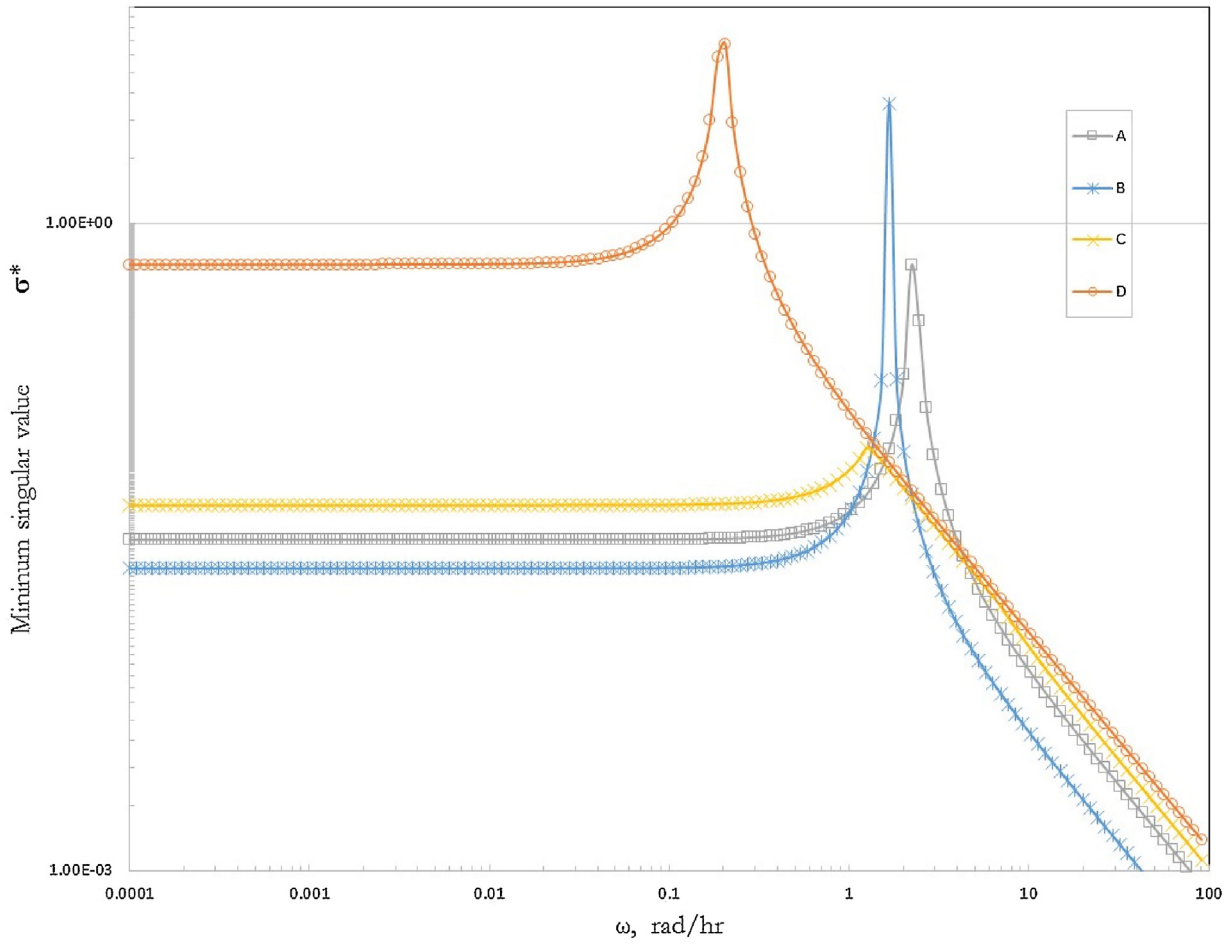

Fig. 20 – Minimum Singular Value for RWDC by the proposed simplified approach.

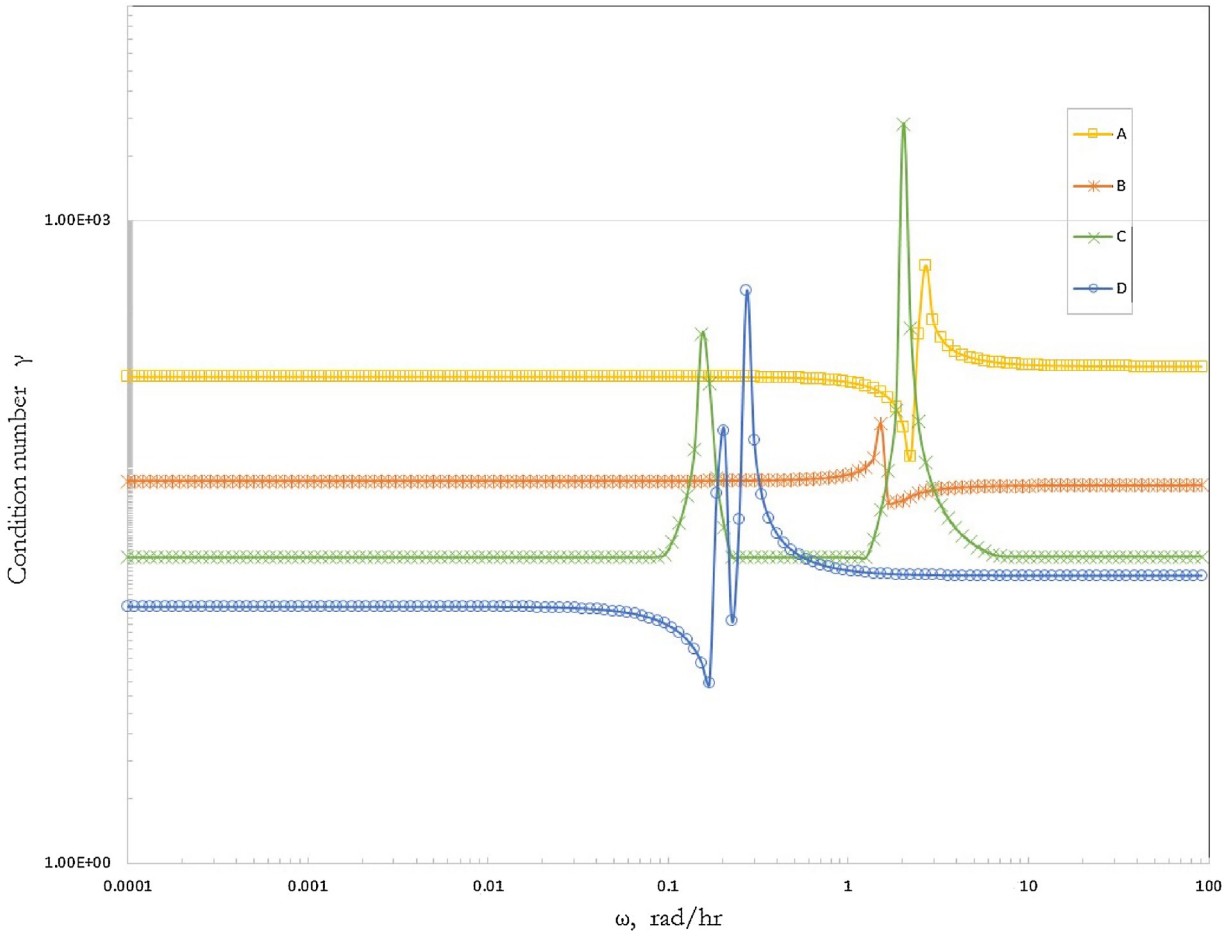

Fig. 21 – Condition Number for RWDC by the proposed simplified approach.

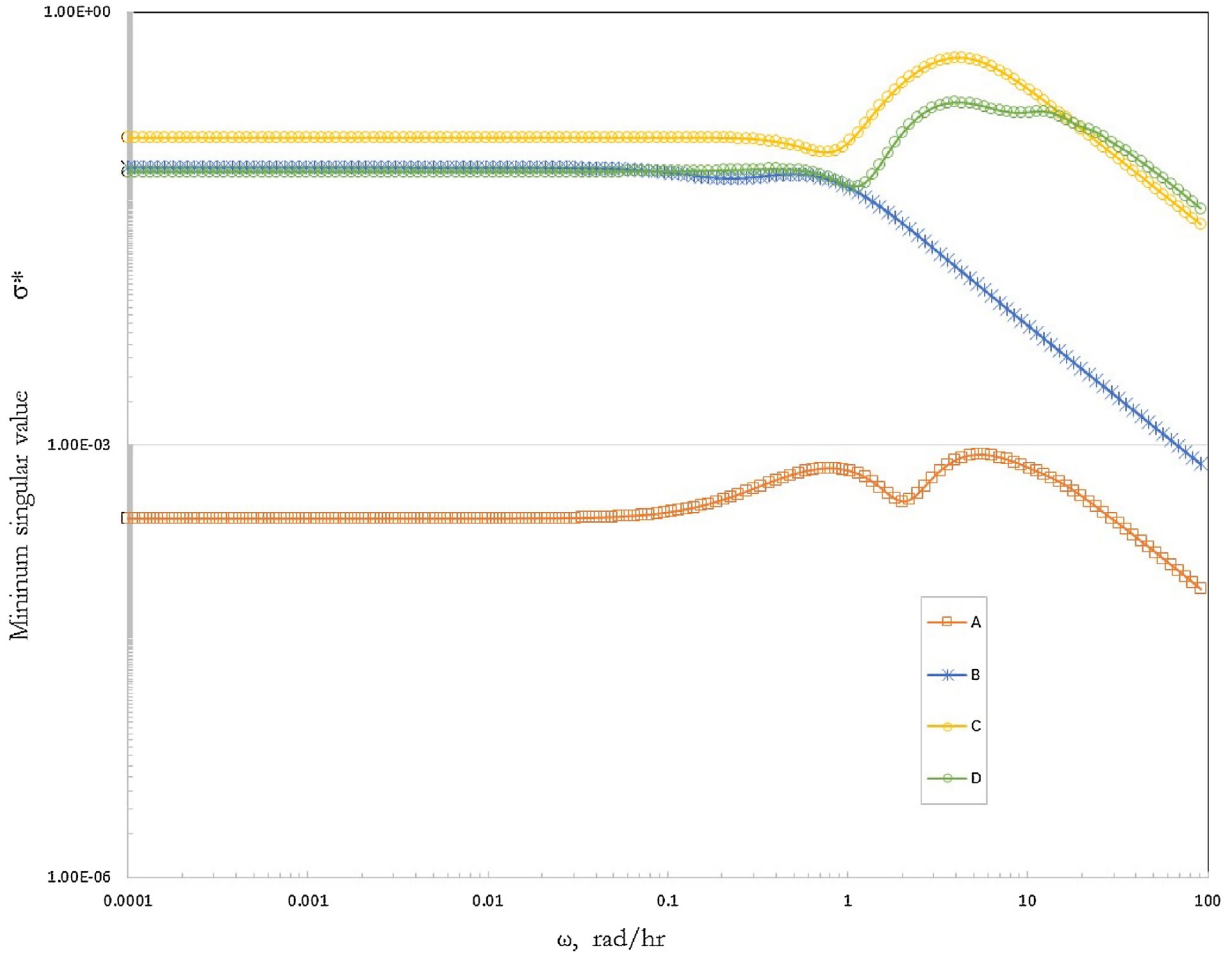

Fig. 22 – Minimum Singular Value for RWDC by the rigorous approach.

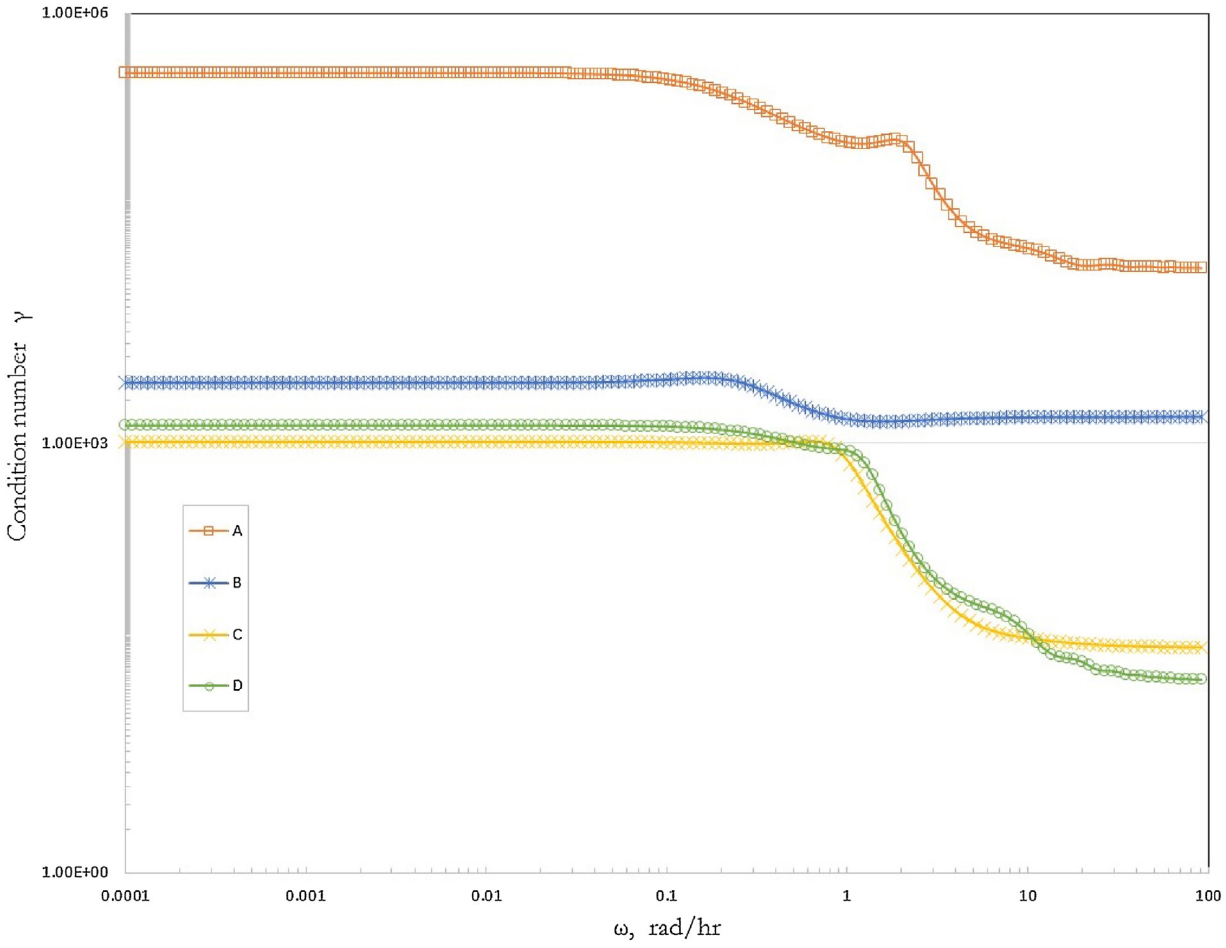

Fig. 23 – Condition Number for RWDC by the rigorous approach.

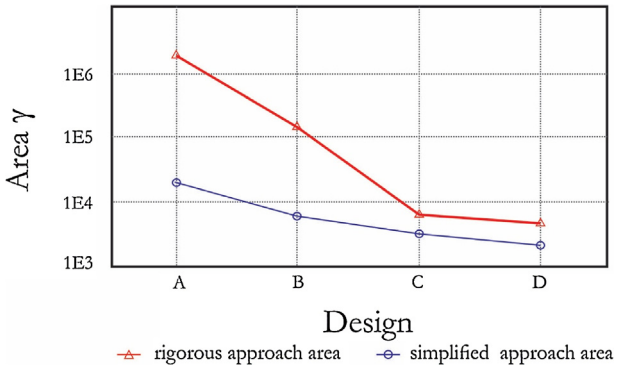

Fig. 24 – Evolution trajectory in the area minimization at several random designs for case RWDC.

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