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TUNING PARAMETERS OF PROPORTIONAL CONTROLLER, INTEGRATOR, DERIVATIVE FOR DISTILLATION TOWER WITH USING MODIFIED PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

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RESUMEN: Dada la importancia del control en la industria, la investigación actual tiene como objetivo la investigación y optimización del controlador PID (Controlador Proporcional-Integral-Derivativo) en uno de los principales equipos industriales de petróleo, gas y petroquímicos, es decir, la torre de destilación. Los parámetros del controlador fueron optimizados utilizando el algoritmo genético codificado en código real y el algoritmo de evolución diferencial y los datos obtenidos se compararon entre sí y con datos obtenidos en un trabajo similar de Wood y Berry para investigar la exactitud. Teniendo en cuenta los resultados, existe una coincidencia aceptable entre los datos obtenidos de los algoritmos y los datos reportados en las referencias, y las simulaciones también indicaron que ambos algoritmos son apropiados para la sintonización sin conexión del controlador PID. Además, los resultados mostraron que el algoritmo genético tiene un rendimiento claramente mejor en el diseño de sistemas de control multivariante.

Palabras clave: regulador PID, torre de destilación, algoritmo genético, algoritmo diferencial

ABSTRACT: Given importance of control in industry, current research aims at investigation and optimization of PID (Proportional–Integral–Derivative Controller) controller in one of the major oil, gas, and petrochemical industrial equipment, i.e. distillation tower. Parameters of the controller were optimized using real-coded genetic algorithm and differential evolution algorithm and obtained data were compared with each other and with data obtained in a similar work by Wood and Berry in order to investigate the accuracy. Considering the results, there is acceptable match between data obtained from both algorithms and data reported in the references, and simulations also indicated both algorithms are appropriate for offline tuning of PID controller. In addition, results showed that genetic algorithm has clearly better performance in designing multivariate controller systems.

Keywords: PID controller, distillation tower, genetic algorithm, differential algorithm

1. INTRODUCTION

Providing optimum conditions and preventing from decline of product properties is one of the most important demands of quality management systems and compliance with quality management standards is one of the main demands of the customers to survive in a highly competitive market. The PID controller is widely used in the petroleum industry. Controlling the process conditions in many reactors, towers, separators, etc. is possible with this control system. Investigation and updating control equipment and systems is one of the major and most economical ways of achieving quality goals. On the other hand, the towers are regarded as one of the most important process equipment in the oil industry, and it can be stated that all processes of oil industry including upstream processes (crude oil processing complexes and gas and liquid gas complexes), intermediate processes (crude oil refining complexes) and downstream processes (petrochemical complexes) occur under influence of this equipment (towers), so that these equipment has become one of the main process equipment in oil industry. Distillation tower is especially important among types of the towers. Thus, optimization and increasing confidence factor in these towers is crucially important/ one of the issues discussed regarding distillation tower is designing PID controller for distillation tower with minimizing a target function like Integral Absolute Error (IAE) [1]. New methods of target function minimizing are based on evolution algorithms (EAs), which have advantage of low computational volume and high speed [2].

Distillation tower has two inputs, U_1 and U_2, and two outputs, Y_1 and Y_2, and Disturbance, $D_{(S)}$. Relationships governing distillation tower are expressed as follows [3].

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$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-s}}{16.7s+1} & \frac{-18.9e^{-3s}}{21.0s+1} \\ \frac{6.6e^{-7s}}{10.9s+1} & \frac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} . \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix} + \begin{bmatrix} \frac{3.8e^{-8.1S}}{10.9s+1} \\ \frac{4.9e^{-3.4S}}{13.2s+1} \end{bmatrix} . \left[D_{(S)} \right] \quad (1)$$

Controller structure is shown in Figure 1 [4].

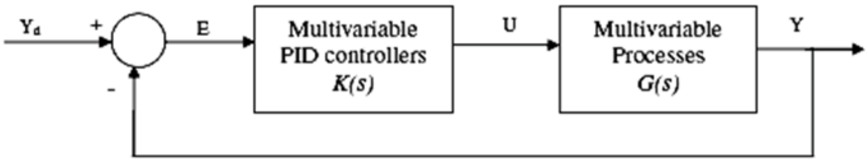

Fig. 1. Multivariate PID controller structure in distillation tower

As shown in Figure 1, vector Y is output vector for a n-dimensional system, which is shown by $Y=\{Y1,\ldots,Yn\}^T$ and vector Y_d is the optimum input vector which is represented by $Y_d=\{Y_{d1},\ldots,Y_{dn}\}^t$ [5]. It should be noted that in Figure 1, $K_{(S)}$ and $G_{(SS)}$ are control coefficient and conversion function.

Error vector and input vector is shown by Equations (2) and (3) [4].

$$E= Y_d - Y = [y_{d1}-y_1, y_{d2} - y_2, \ldots, y_{dn} - y_n]^T = [E_1, E_2, \ldots, E_n]^T \quad (2)$$

$$U=[U_1.U_2,\ldots,U_n]^T \quad (3)$$

It should be noted that PID controller parameters are given as a diagonal matrix in Equation (4) [5].

$$\mathrm{K(s)} = \begin{bmatrix} K_1(s) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathrm{K_n(s)} \end{bmatrix} \quad (4)$$

Where:

$$K_i(S) = K_{pi} + \frac{K_{Ii}}{S} + K_{Di} S \quad (5)$$

Target function is defined as integral error absolute in designing coefficients of K_{Pi}, K_i, and K_{Di} [5]. Target function (Integral Absolute Error), which is abbreviated as IAE, is calculated using Equation (6).

$$IAE = \int_0^\infty (|e_1(t)| + |e_2(t)| + \ldots + |e_n(t)|) dt \quad (6)$$

Since process function of distillation tower is two inputs and two outputs, using Equation (5), six parameters of K_P . K_I . K_D for input and output are selected by differential evolution and genetic algorithms in such a way that target function is minimized [5].

2. DISCUTION

In this section, it is attempted to examine performance of real-coded genetic algorithm (GA) and differential evolution algorithm (DE) on optimum design of multivariate PID controller. Structure of multivariate PID and PI (Proportional integral) controller for double distillation tower which was explained by Wood and Berry [5], is considered as having two inputs and two outputs. Simulation of EAs is done with reduction of IAE as the goal using two types of stationary conditions, namely, maximum functional value (Fevalmax) and Fevalmax with the allowed error of PID and IAE parameters. For comparing performance of different evolution algorithms, statistical calculations such as standard deviation, average, and the best of the results and average calculation time, were considered on more than 20 independent tests. Results obtained from evolution DE and GA algorithms were compared with the results previously reported by Wood and Berry [5] using multi-structural view.

2.1. Data Obtained from Simulation Using Genetic Algorithm

Table 1 gives data obtained in the optimization process by genetic algorithm. It should be mentioned that optimization process by genetic algorithm was done in 200 steps.

Table 1. Data obtained from simulation of distillation tower using evolution genetic algorithm

Parameters	**GA (Run 1)**	**GA (Run 10)**	**GA (Run 50)**	**GA (Run 100)**	**GA (Run 200)**
Kp1	0.1993	0.1993	0.1993	0.1993	0.1993
Ki1	0.0361	0.0361	0.0361	0.0361	0.0361
Kd1	0.0446	0.0446	0.0446	0.0446	0.0446
Kp2	-0.2545	-0.2545	-0.2545	-0.2545	-0.2545
Ki2	-0.0092	-0.0092	-0.0092	-0.0092	-0.0092
Kd2	-0.4695	-0.4695	-0.4695	-0.4695	-0.4695
e 1	2.6665E+00	1.207E+00	4.933E+00	2.984E+00	8.690E-01
e 2	3.0704E+00	8.658E+16	9.328E+10	3.711E+05	9.561E+03
IAE (y1)	5.3560E+00	8.890E+11	9.230E+09	5.341E+05	1.655E+05
IAE(y2)	5.1015E+00	9.541E+13	9.218E+11	5.100E+06	1.053E+05
Minimum	1.107E+01	8.147E+00	5.192E+00	2.613E+00	8.325E-01
Maximum	1.1068E+01	9.8348E+00	5.8021E+00	2.3544E+00	1.0342E+00
Mean	1.1068E+01	8.9909E+00	5.4971E+00	2.4837E+00	9.3335E-01
Time (min)	3	40	105	185	300

As observed, each step has two inputs and maximum, minimum, and average of target function. Simulation process lasts for 300 minutes and when difference of data related to two sequential steps is trivial or when simulation time is ended, the final answer is reached.

In order to ensure accuracy of simulation, data obtained from the final step (200^{th} step) are compared with data from Wood and Berry's work in Table 2.

Table 2. Comparison of data obtained from simulation using evolution genetic algorithm and reports in references [5]

Parameters	**End Of Simulation Data (Run 200) (GA)**	**Reference Essay (Wood & Berry)**
Kp1	1.99E-01	1.99E-01
Ki1	3.61E-02	3.61E-02
Kd1	4.46E-02	4.46E-02
Kp2	-2.55E-01	-2.55E-01
Ki2	-9.20E-03	-9.20E-03
Kd2	-4.70E-01	-4.70E-01
e 1	8.69E-01	7.50E-01
e 2	9.56E+03	9.23E+03
IAE (y1)	1.66E+05	1.65E+05
IAE(y2)	1.05E+05	1.05E+05
Minimum	8.33E-01	8.17E-01
Maximum	1.03E+00	1.11E+00
Mean	9.33E-01	9.65E-01

As observed in Table 2, maximum, minimum, and mean values of target function are higher than values reported in the reference with identical input values. In addition, disturbance in simulation with genetic algorithm is smaller than results reported in reference [5].

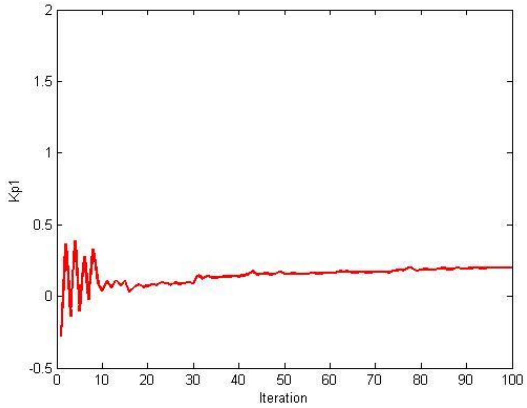

Fig. 2. Kpl value in initial, intermediate, and final steps of simulation process

As observed in Figure 2, Kpl value has high changes with short range at the beginning of simulation process by genetic algorithm, and range of changes is reduced and it becomes almost linear over the time with progress of simulation process.

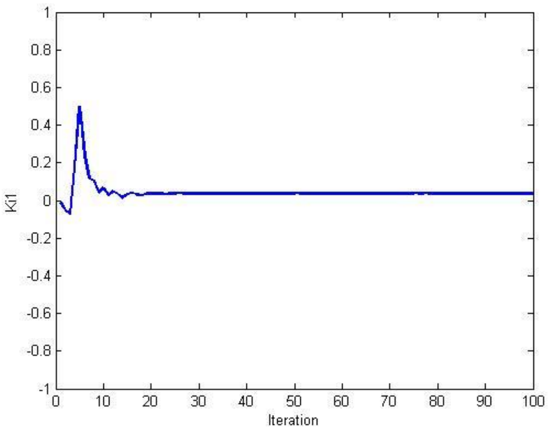

Fig. 3. Kil value in initial, intermediate, and final steps of simulation process

According to data shown in Figure 3, Kil value has high mutation with short range at the beginning of simulation process by genetic algorithm, and range of changes is reduced and it becomes almost linear over the time with progress of simulation process.

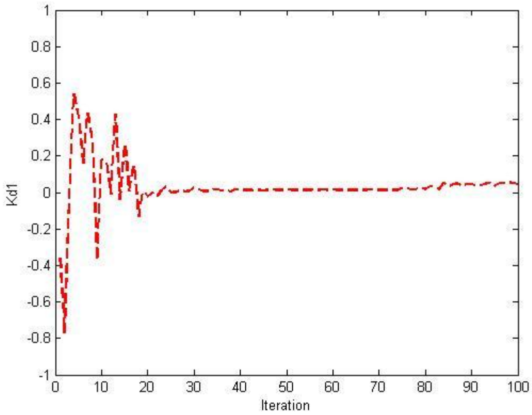

Fig. 4. Kdl value in initial, intermediate, and final steps of simulation process

As observed in Figure 4, Kpl value has high changes with wide range at the beginning of simulation process by genetic algorithm, and range of changes is reduced over the time and it tends to 0.0446 at the end of simulation process.

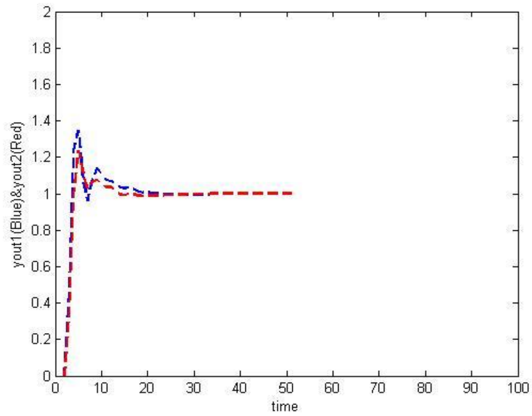

Fig. 5. Changes in disturbance 1 and 2

As observed in Figure 5, changes in YOUT1 and YOUT2 (disturbance 1 and 2) is high at the beginning of simulation process by genetic algorithm, which reduce over the time with progress of simulation time in line with increasing optimum system performance.

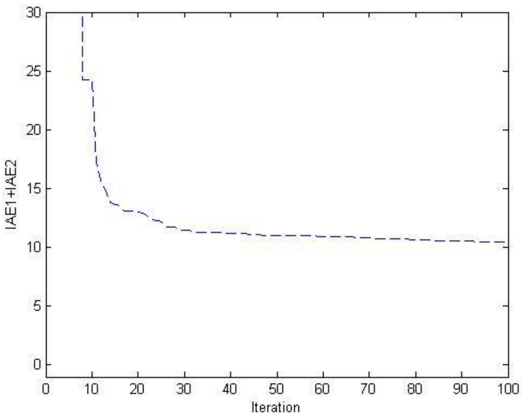

Fig. 6. Changes in total error 1 and 2

According to Figure 6 and unlike previous figures, changes in IAE1 and IAE2 (total error 1 and 2) are high at the beginning of simulation process by genetic algorithm (GA), which reduce with progress of simulation as step-wise with wide range. It is in line with increasing optimum system performance and total error values are reduced and reach to very small values.

2.2. Data Obtained from Simulation Using Differential Algorithm

In this section, data obtained from distillation tower simulation using differential algorithm and diagrams of first and last steps of simulation process are given. It is noted that the simulation by differential algorithm was run in 200 steps.

Table 3. Data obtained from distillation tower simulation using differential algorithm

Parameters	**DE (Run 1)**	**DE (Run 10)**	**DE (Run 50)**	**DE (Run 100)**	**DE (Run 200)**
Kp1	0.8478	0.8478	0.8478	0.8478	0.8478
Ki1	0.3529	0.3529	0.3529	0.3529	0.3529
Kd1	0.1765	0.1765	0.1765	0.1765	0.1765
Kp2	-0.0633	-0.0633	-0.0633	-0.0633	-0.0633
Ki2	-0.0524	-0.0524	-0.0524	-0.0524	-0.0524
Kd2	-0.1993	-0.1993	-0.1993	-0.1993	-0.1993
e 1	3.0397	2.8546	2.0071	1.531	0.9856
e 2	16.3747	14.7134	11.7991	9.6035	8.4539
IAE (y1)	6.1902	5.7321	4.7861	3.9804	2.9421
IAE(y2)	20.725	17.082	13.442	9.375	7.451
Minimum	6.917	6.027	5.614	4.961	4.001
Maximum	6.917	6.027	5.614	4.961	4.001
Mean	6.917	6.03E+00	5.61E+00	4.96E+00	4.00E+00
Time (min)	8	35	115	220	310

It is clear that similar to simulation with genetic algorithm, each step has two inputs and disturbance reduces during simulation process, and it decreases over the time so that it reaches to acceptable value at the end of process. As observed in Table 3, maximum and minimum values of target function also reduce during the process. In order to examine accuracy of data, values obtained from differential algorithm simulation in the last step and reference data [5] are compared in Table 4.

Table 4. Comparison of data obtained from simulation using differential algorithm and reports in reference [5]

Parameters	**End Of Simulation Data (Run 200) (DE)**	**Reference Essay (Wood & Berry)**
Kp1	0.8478	0.8478
Ki1	0.3529	0.3529
Kd1	0.1765	0.1765
Kp2	-0.0633	-0.0633
Ki2	-0.0524	-0.0524
Kd2	-0.1993	-0.1993
e 1	0.9856	1.0146
e 2	8.4539	8.8896
IAE (y1)	2.9421	3.3451
IAE(y2)	7.451	7.998
Minimum	4.001	4.381

Maximum	4.001	4.381
Mean	4.00E+00	4.381

Data in table 4 illustrates that results obtained from optimization of distillation tower control factors by differential algorithm and reference results [5] have good match. It should be mentioned that error resulting from simulation by differential algorithm, like genetic algorithm, is less than data reported by Wood and Berry. Thus, the final answer is more accurate.

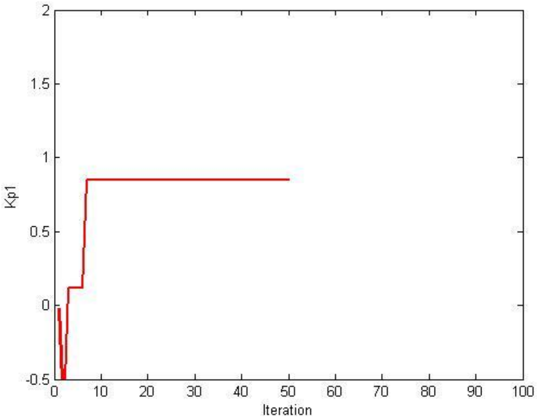

Fig. 7. Kpl in initial, intermediate, and final steps of simulation process

Figure 7 shows Kpl value during simulation process. At the beginning of simulation process by differential algorithm (DE), changes were step-wise, and the changes reduced over the time and got linear at the end of simulation process.

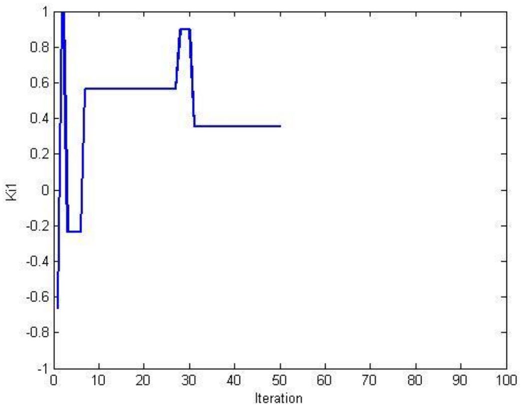

Fig. 8. Kil value in initial, intermediate, and final steps of simulation process

Figure 8 gives informations about Kil value during simulation process. It can be seen that Kil changes at the beginning of simulation process by differential algorithm (DE) was step-wise, but it went down over the time at the final steps of the process, and finally it reached to 0.3529.

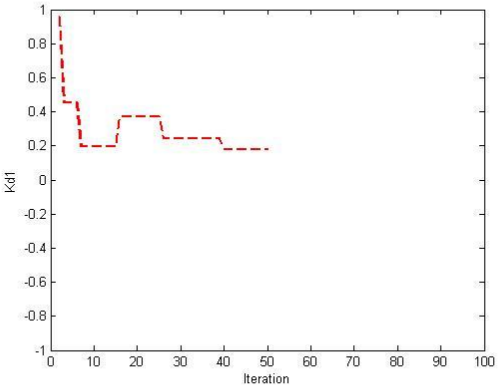

Fig. 9. Kdl value in initial, intermediate, and final steps of simulation process

As observed in Figure 9, Kpl value has step-wise changes with short range at the beginning of simulation process by differential algorithm, and range of changes is decreased over the time and it becomes almost linear at the last step in line with zero limiting.

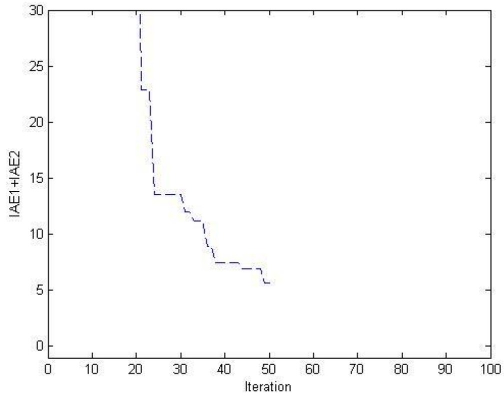

Fig. 10. Changes in total error 1 and 2

It is cleared in Figure 10 that values IAE1 and IAE2 (total error 1 and 2) are high at the beginning of simulation by differential algorithm, which get step-wise with progress of simulation time, and it is in wide range. Total error values reduce in line with increasing optimum system performance.

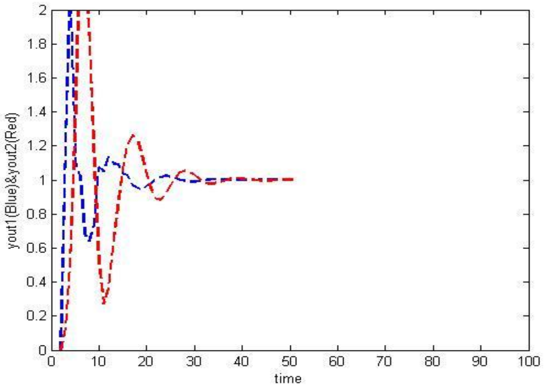

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Fig. 11. Changes in total disturbance 1 and 2

Figure 11 demonstrate that YOUT1 and YOUT2 (disturbance 1 and 2) values are high at the beginning of simulation process by differential algorithm, which reduce over the time with progress of simulation time in line with increasing optimum system performance.

The considerable point in investigation of diagrams of genetic algorithm (GA) and differential evolution (DE) algorithm is related to changes of values. Trend of changes in input and output values of simulation process in genetic algorithm (GA) is with high slope and wide range, while the changes in differential algorithm is step-wise with lower slope and range.

3. CONCLUSION

One of the main results obtained from simulation is superiority of differential algorithm over genetic algorithm (in terms of similarity of obtained values to the values in the main paper (Wood and Berry)). The other finding is shorter computational time using genetic algorithm, reduced material durability in the tower (reducing process time), increasing purity of tower's top product, and reducing steam required for the separation process.

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