MODEL-FREE ADAPTIVE CONTROL WITH TUNED PARAMETERS BY MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION

JUDAS, T. G., SOUSA

Colegiado de Engenharia Civil, Universidade Federal do Vale do São Francisco - UNIVASF
Av. Antonio Carlos Magalhãoes, 510, CEP: 48902-300, Juazeiro, BA, Brasil
E-mails: judas.tadeu@univasf.edu.br

ALUIZIO, F. R. , ARAUJO

Centro de Informática, Universicade Federal de Pernanbuco - UFPE
Av. Jorn. Anibal Fernances, SN, CEP 12345-678, Recife, PE, Brasil
E-mails: aluizioa@cin.ufpe.br

Abstract— In recent decades, the development of model free control techniques, whose control is based on measured data during the execution of the process, has intensified. In this context, the data-driven control technique called Model-Free Adaptive Control has been highlighted because its applications include linear and nonlinear systems, SISO or MIMO. In this paper, we dealt with an open question in this technique, which is the choice of controller parameters that provide better performance to the control system. To solve this problem, we used a metaheuristic based in a multi-objective differential evolution algorithm to tune the controller parameters. The results confirmed the validity of the proposed strategy, to define the controller parameters, for examples already presented in the literature.

Keywords— Data-driven control, Model-free adaptive control, Nonlinear systems, Multi-objective optimization, Differential evolution.

Resumo— Nas últimas décadas, intensificou-se o desenvolvimento de técnicas de controle livre de modelo, cujo controle é baseado nos dados medidos durante a fase de operação do processo. Neste contexto, a técnica de controle baseada em dados, denominada Controle Adaptativo Livre de Modelo, tem sido destacada porque suas aplicações incluem sistemas lineares e não-lineares, SISO ou MIMO. Neste artigo, abordamos uma questão aberta nesta técnica, que é a escolha dos parâmetros do controlador que fornecem melhor desempenho ao sistema de controle. Para resolver esse problema, usamos uma metaheurística baseada no algoritmo de evolução diferencial multi-objetivo para ajustar os parâmetros do controlador. Os resultados confirmaram a validade da estratégia proposta, para definir os parâmetros do controlador, para exemplos já apresentados na literatura.

Palavras-chave— Controle baseado em dados, Controle adaptativo livre de modelo, Sistemas não-lineares, Otimização multi-objetivo, Evolução diferencial.

1 Introduction

The complexity of modern industrial processes affects the use of control techniques based on models, e.g., Linear Quadratic Control, Robust Control, and Stochastic Control, whose efficiency is closely related to the hypothesis that the dynamics of the model used in the controller design must behave as the actual system. However, the conception of the model is normally based on abstractions, which may cause errors to the control design, reason for undesired behavior of the controlled system. One can increase the complexity of the model, resulting in more complex controllers, which are more difficult to design and use in practical situations. Moreover, this option does not eliminate the possibility of failure due to absence of matching between the model and the real plant.

Currently, control techniques that are model free and simple to be implemented and maintained are desired. The increased capacity of handling data of modern industrial processes, has allowed the development of a number of control techniques, that are based on data collected during the operating phase. Nowadays, these techniques are part of a new branch of control theory called Data-Driven Control – DDC (Hou and Wang, 2013).

Amongst the DDC families of models, the technique called Model Free Adaptive Control - MFAC stands out for its flexibility, with applications to control nonlinear, time-varying, SISO and MIMO systems (Hou and Jin, 2014). In addition, the MFAC can adjust the design of the controller according to the degree of complexity of an actual system and its structure allows the combination of MFAC with other model-free or model-based control techniques.

The MFAC was introduced by Hou and Huang (1997) for SISO systems, with the premise of building in every operating point a dynamic linearized model of the plant, considering an estimation of the Pseudo Partial Derivative - PPD. In the method, the PPD and the corresponding control signal are calculated using only the I/O data of the plant and the reference signal.

After that, the MFAC has received several contributions in this theory. For example, Hou and Jin (2011) demonstrated the application of MFAC for

MIMO systems and proved the stability for regulation problems in some cases. In 2013, Hou and Zhu, extended the concept of dynamic linearization to the controller, defining an optimal dynamic linear controller that vanishes the error signal in the future. Leng et al (2014) presented a concept of contractive MFAC, by the introduction of a contraction constrain to force the error signal to decay exponentially. In this strategy, the MFAC control became an optimization problem using quadratic programming.

The combination of the MFAC with other techniques has also been addressed in the literature. For example, Jalali et al (2013) used a MFAC Fuzzy Sliding Mode controller optimized by Particle Swarm Algorithm to control a robot manipulator. Bu et al (2013) presented the validity of combination of the MFAC with Interactive Learning Control technique (MFAILC) for path control of a farm vehicle. Xu et al (2014) used the concept of State Observer for PPD matrix estimation in MIMO systems. Zhu and Hou (2014) presented the combination of MFAC and neural networks with radial basis function kernel.

Parameter tuning of MFAC is currently an open problem; the choice of values affects the control performance. In 2014, Ji et al tuned their MFAC controller parameters using the concept of minimum entropy. Sousa et al (2015) presented the off-line optimization of MFAC parameters for SISO systems, using a differential evolution multi-objective optimization algorithm. Recently, Roman et al (2016) addressed the tuning of controller parameters, combining MFAC with other DDC technique called Virtual Reference Feedback Tuning for MIMO systems.

The design of a control system is often a challenge because it may require a number of decision criteria. This multiplicity added difficulty to apply conventional optimization tools for control design of the problems with the treatment of nonlinear and stochastic systems, favoring the use of meta-heuristics such as Evolutionary Algorithms - EA to solve these problems (Reynoso-Meza et al, 2013).

In this paper, we present the integration between MFAC and multi-objective EAs for off-line tuning of the controller parameters. This article is a continuation of the work presented by Sousa et al (2015), but here the estimated initial PPD is added to problem of MFAC parameter optimization. Moreover, a new objective function is introduced, aiming to reduce the overshoot of the output signal, and a new case using this strategy is tested. The performance of the optimal parameters and other parameters found in the literature is compared using the Pareto dominance criterion.

2 Model Free Adaptive Control - MFAC

The DDC technique Model-Free Adaptive Control - MFAC uses the I/O data measured from the process to consider the dynamic linear behavior for the plant at each instant. The MFAC theory employs the concept of Pseudo Partial Derivative - PPD, an estimate of the partial derivative of the equation for the plant, calculated at a certain operation point. Unfortunately, the PPD cannot be calculated analytically, however, it can be estimated using the I/O data. Based on that, the MFAC uses the linear dynamic model generated to calculate the control signal to the real system.

2.1 A Discrete-time Nonlinear System

Consider a nonlinear, discrete time, and SISO system described by:

$$y(k+1) = f\,(y(k),...,y(k-n_y),u(k),...,u(k-n_u)) \quad (1)$$

where, $u(k)$ and $y(k)$ are the input and output of the system, at time instant k, and n_u and n_y are two unknown positive integers, and $f(...)$ is an unknown nonlinear function.

2.2 Assumptions

The system (1) satisfies the generalized Lipschitz condition or similar conditions (Hou and Wang, 2013), for all k fixed:

$$|\Delta y(k+1)| \leq b|\Delta u(k)| \quad (2)$$

where $b > 0$ is a constant, $\Delta y(k+1) = y(k+1) - y(k)$ and $\Delta u(k) = u(k) - u(k-1) \neq 0$. Then (1) can be expressed as a dynamic linearization data model, and the PPD is uniformly bounded.

2.3 Compact Form Dynamic Linearization – CFDL

For SISO systems, the MFAC theory presents three dynamic linearization data models (Hou and Jin, 2014). In this paper, we considered only the Compact Form Dynamic Linearization – CFDL :

$$y(k+1) = y(k) + \phi(k)\Delta u(k) \quad (3)$$

where ϕ(k) is the PPD at k instant.

2.4 Control scheme CFDL-MFAC

Hou and Jin (2014) presented the following scheme for CFDL-MFAC. At each k instant, first estimate the PPD using (4):

$$\hat{\phi}(k) = \hat{\phi}(k-1) + \frac{\eta \Delta u(k-1)\left(\Delta y(k) - \hat{\phi}(k-1)\Delta u(k-1)\right)}{\mu + \Delta u(k-1)^2} \quad (4)$$

where $\mu > 0$ and $\eta \in (0,2]$ are two parameters added to give more flexibility to the PPD estimation algorithm. Considering the following resetting conditions:

$$\hat{\phi}(k) = \hat{\phi}(1), if \ \left|\hat{\phi}(k)\right| \le \varepsilon \ or \ \left|\Delta u(k-1)\right| \le \varepsilon \\ or \ sign(\hat{\phi}(k)) \ne sign(\hat{\phi}(1)) \tag{5}$$

where ε is a small positive constant and $\hat{\phi}(1)$ is the initial value for estimated PPD.

Then the control signal can be determined as

$$u(k) = u(k-1) + \frac{\rho\hat{\phi}(k)}{\lambda + \left|\hat{\phi}(k)\right|^2}\left(y^*(k+1) - y(k)\right) \tag{6}$$

where $y^*(k+1)$ is the desired output signal and $\lambda>0$ and $\rho\in(0,1]$ are controller parameters.

Very often, the choice of all these parameters and $\hat{\phi}(1)$ is made only according to qualitative analysis. Therefore, in this article we propose to turn the design problem of the controller in a multi-objective optimization problem.

3 Multi-objective Differential Evolution

3.1 Multi-objective Optimization Problem (MOP)

A general MOP can be defined as a search for each $\mathbf{x} = [x_1\ x_2\ \ldots\ x_n]^T$ within a decision space D, which satisfies a feasible region (FR) defined by the constraints of m inequalities:

$$g_i(\mathbf{x}) \ge 0;\ \ i = 1, \ldots, m \tag{7}$$

and by p equalities:

$$h_i(\mathbf{x}) = 0;\ \ i = 1, \ldots, p \tag{8}$$

while optimizing the vector of objective functions:

$$\mathrm{Min}([f_1(\mathbf{x})\ f_2(\mathbf{x})\ ..,\ f_k(\mathbf{x})]^T) \tag{9}$$

The complete solution of a MOP is expressed by the Pareto front which is built using the dominance criterion (Coello et al, 2007). A solution $\mathbf{x}_1$ is said to dominate another solution $\mathbf{x}_2$ if the following conditions are satisfied:

$$\forall\ i\in(1,2,..,k)\ |\ f_i(\mathbf{x}_1) \le\ f_i(\mathbf{x}_2) \tag{10}$$
$$\exists\ i\in(1,2,..,k)\ |\ f_i(\mathbf{x}_1) <\ f_i(\mathbf{x}_2) \tag{11}$$

that is, $\mathbf{x}_1$ is better than or equal to $\mathbf{x}_2$ in all objectives $f_1(\mathbf{x})$, $f_2(\mathbf{x})$,.., $f_k(\mathbf{x})$, but strictly better in at least one of objectives.

3.2 Multi-Objective Differential Evolution Algorithm

We propose a Multi-Objective Differential Evolution Algorithm - MODEA, based on the previous approach proposed by Sousa et al (2015) to solve the Multi-Objective Problem - MOP. In this current version, the MODEA is a memetic version in which the random initial population with NP individuals is duplicated using the corresponding set of symmetric opposite vectors. Then, the population is again reduced to NP individuals in accordance with a nondomination rank criterion and a crowding distance metric.

The nondomination ranking is constructed by comparing all individuals so as to determine the number of solutions dominated by each solution in the population. The nondominated individuals found in this process form the front F_1. Next, after removing individuals in F_1 from the population, the remaining individuals are evaluated to form the front F_2. This process is repeated to form the other fronts so as to include all individuals.

The ordering for individuals in a same front is made using the decreasing value of Crowding-Distance - CD (Ali et al, 2012). To calculate this distance, the population is initially sorted in accordance with the value of each objective function, normalized in ascending order of magnitude. Thereafter, for each objective function, the solutions with the smallest and largest function values are assigned as an infinite distance value. For each other solution we calculate a distance value, the absolute normalized difference in the function values of two adjacent solutions, which is determined for all objective functions. The overall crowding-distance is the sum of the individual distances corresponding to each objective function.

After initialization, the algorithm follows the steps of the standard Differential Evolution (DE) algorithm, i.e., in each generation, there is a crossover between each mutant and its target vectors so as to produce a trial vector. However, for a multi-objective problem, the selection process is different. In this case, we use the procedure presented in Abbass et al (2001), called, the Pareto Differential Evolution Approach (PDEA), i.e., the targets vectors come from the current population and the trial vectors come from the advance population. These two populations are grouped in a total population of 2NP individuals. Then, using a procedure similar to that used in the initialization stage, the population is reduced to NP individuals, the next generation. The procedure is repeated until the stop criterion is reached.

To promote more diversity in the population of solution candidates, two changes were implemented in the proposed MODEA algorithm. Firstly, for each mutant vector generated so also was its opposite symmetric vector. Finally, the mutant vector only generates the trial vector if this is not dominated by its opposite vector, in which case, the latter is used for the crossover.

Secondly, to spread the current nondominated solutions, the individuals of the advance population were replaced by others generated both randomly and based on the criterion of the opposite vector. This occurs every pre-determined number of generations.

3.3 MODEA - Algorithm

1. Generate initial population P_0 with *NP* random vectors;
2. Calculate its symmetric opposed population P_{op};
3. Merge the two populations $P_{dup} = P_0 \cup P_{op}$;
4. Create a nondominant ranking for P_{dup};
5. Select *NP* vectors using the ranking and the *CD*;
6. Initialize the generation count;
7. While stop condition is not satisfied;
8. Form a current population using the selected vectors P_{cur};
9. For each vector of current population;
10. Choose three others vectors;
11. Combine the three vectors to form a mutant vector;
12. Mate the mutant vector with the current individual;
13. The trial vector resulting is add to advance pop P_{adv};
14. End for;
15. Actualize the generation count;
16. If the generation count is multiple of *K*;
17. Generate *NP* random and opposite symmetric vectors;
18. Substitute the advance population for these;
19. End if;
20. Merge the populations P_{cur} and P_{adv};
21. Create a nondominant ranking for all vectors;
22. Select *NP* vectors using the ranking and the *CD*;
23. Increment the generation count;
24. Evaluate the stop condition;
25. End while;
26. Generate the Pareto front estimated;
27. Define the solution using Decision Maker - DM.

4. Evolutionary Model-Free Adaptive Control

4.1 Proposed scheme

In this paper, the MODEA is used to tune off-line the MFAC controller parameters. In the algorithm, the individuals that form the population of solutions to MOP are real-valued vectors in which each gene is a controller parameter, ρ, μ, η, and λ, and $\hat{\phi}(1)$. For the evolutionary process, the fitness calculation for each individual is based on the response of the controlled system, by simulating the system off-line, using each individual as the set of parameters for the MFAC controller.

4.2 The Objective Functions

For the optimization, two objective functions were considered:

$$f_1(y^*(k), y(k)) = \frac{1}{N}\sum_{k=1}^{N}\left[(e(k))^2\right] \qquad (12)$$

and

$$f_2(y^*(k), y(k)) = \frac{1}{N-1}\sum_{k=1}^{N-1}\left[(e'(k))^2\right] \qquad (13)$$

where $e(k) = y^*(k) - y(k)$ is the error signal, $e'(k)$ is the error signal derivative.

These two functions represent different control objectives. Function (12) is defined by means of the accumulative squared error signal, which is a variable that is used to reduce the error of the steady state. Function (13), on the other hand, is calculated by means of the accumulative squared error signal derivative. This seeks to reduce the maximum error during the transient state.

4.3 Decision-Maker

As a result of the evolutionary process, a set of nondominated solutions that approximates the Pareto front are determined. The choice of a particular solution was based on the criterion of the smallest Euclidian distance between each solution on the Pareto front and the utopia point, the solution that takes the two normalized objective functions to zero:

$$x_{chosen} = \min_{1 \le i \le NP}\left(d(x_i)\right); d_i = \sqrt{f_{N1}(x_i)^2 + f_{N2}(x_i)^2} \qquad (14)$$

where x_{chosen} is the solution adopted, and $f_{N1}(x_i)$ and $f_{N2}(x_i)$ are the normalized objective functions.

5. Results

In this Section, we present the solutions obtained by the evolutionary algorithm and the controlled system response using the parameters chosen for two examples.

In all cases the MODEA has the following internal parameters: weighting factor for mutation F = 0.50; crossover rate Cr = 0.80; number of population elements: NP = 100; maximum number of generations 2000; generation interval for replacing the advance population: K = 250.

The initial conditions for the two examples, according to (Hou and Jin, 2014), are $u(1) = u(2) = 0$, $y(1) = -1$, $y(2) = 1$ and $\varepsilon = 10^{-5}$.

5.1 Example 1

A nonlinear system that consists of two subsystems in series (Hou and Jin, 2014):

$$y(k+1) = \begin{cases} \dfrac{y(k)}{1+y^2(k)} + u^3(k), & k \le 500 \\ \dfrac{y(k)y(k-1)y(k-2)u(k-1)(y(k-2)-1)+a(k)u(k)}{1+y^2(k-1)+y^2(k-2)}, & k > 500 \end{cases} \qquad (15)$$

where $a(k)$ = round(k/500).

The desired output signal is:

$$y^*(k+1) = \begin{cases} 0.5(-1)^{round(k/100)}, & k \le 300 \\ 0.5\sin(k\pi/100) + 0.3\cos(k\pi/50), & 300 < k \le 700 \\ 0.5(-1)^{round(k/100)}, & k > 700 \end{cases} \quad (16)$$

After MODEA optimization, the Figure 1 presents the Pareto front obtained using normalized objective functions.

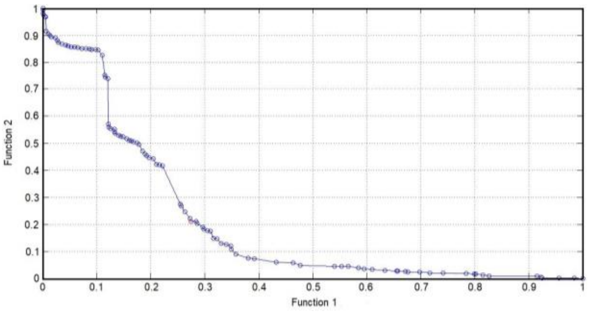

Figure 1. The Pareto front and nondominated solutions

Using the DM criterion, the following controller parameters were found: ρ = 0.9941, η = 1.9939, μ = 0.3853, and λ = 0.0938, and $\hat{\phi}(1) = 0.8583$.

In Figure 2, the outputs of the controlled system and the reference signal, for the chosen parameters and three other set of parameters found in the literature (Hou and Jin, 2014; Sousa et al, 2015) are presented.

The Table 1 presents the values of objective functions calculated and the values for the set of corresponding parameters:

Table 1. Objective Functions Values

Parameters [ρ; η; μ; λ; $\hat{\phi}(1)$]	Set	f_1	f_2
[0.9941;1.9939;0.3853;0.0938;0.8583]	DM	0.0073	0.0086
[0.6; 1; 1; 0.1; 2]	1	0.0169	0.0121
[0.6; 1; 1; 2; 2]	2	0.0265	0.0117
[0.9913;1.537;0.1733; 2.1536; 2]	3	0.0195	0.0114

4.2 Example 2

Again, a nonlinear system that consists of two subsystems in series (Hou and Jin, 2014):

$$y(k+1) = \begin{cases} \dfrac{5y(k)y(k-1)}{1+y^2(k)+y^2(k-1)+y^2(k-2)} + u(k) + 1.1u(k-1), & k \le 500 \\ \dfrac{2.5y(k)y(k-1)}{1+y^2(k)+y^2(k-1)} + 1.2u(k) + 1.4u(k-1) & \\ +0.7\sin(0,5(y(k)+y(k-1)))\cos(0,5(y(k)+y(k-1))), & k > 500 \end{cases} \quad (17)$$

The desired output signal is:

$$y^*(k+1) = \begin{cases} 5\sin(k\pi/50) + 2\cos(k\pi/100), & k \le 300 \\ 5(-1)^{round(k/100)}, & 300 < k \le 700 \\ 5\sin(k\pi/50) + 2\cos(k\pi/100), & k > 700 \end{cases} \quad (18)$$

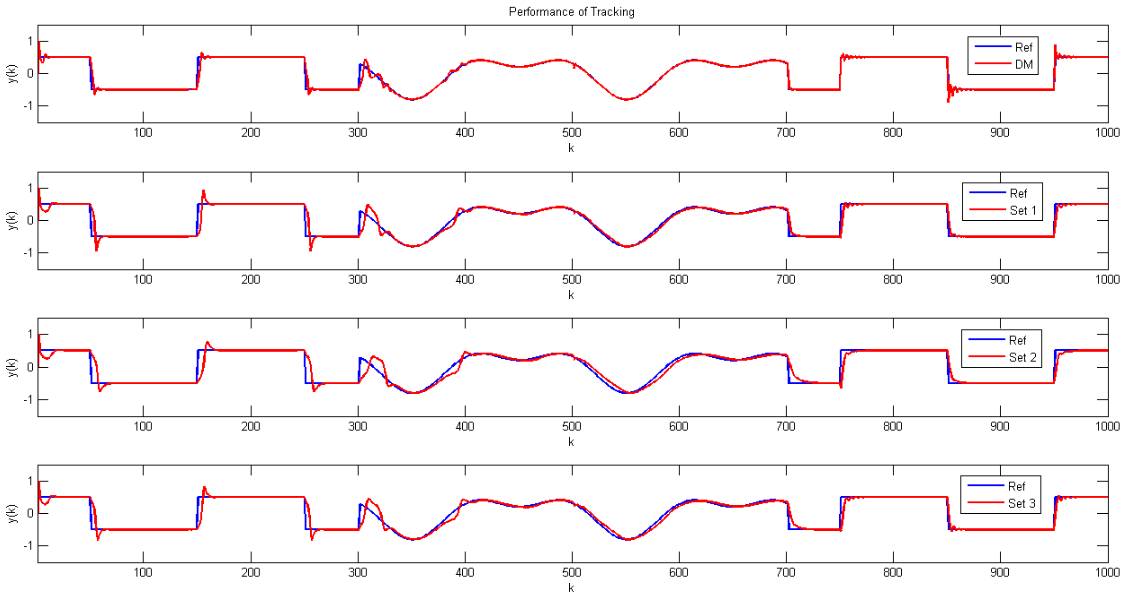

Figure 2. Graphics records of the reference signal and response of the controlled system using four set of parameters.

The Figure 3 presents the Pareto front obtained.

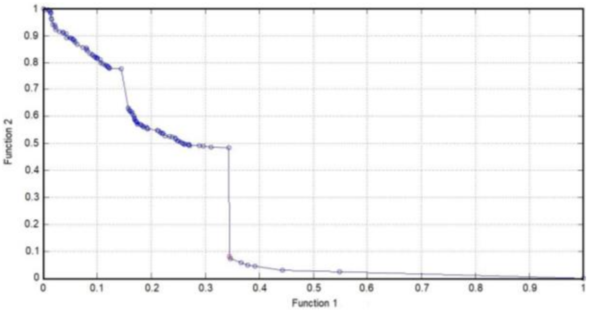

Figure 3. The Pareto front and nondominated solutions

Using the DM criterion, the following controller parameters were found: ρ = 0.8877, η = 1.9888, μ = 0.0257, and λ = 1.8762 and, $\hat{\phi}(1)$ = 2.0157.

The outputs for the controlled system and the reference signal using the chosen parameters and more two other set of parameters found in the literature (Hou and Jin, 2014), can be observed in Figure 4.

The Table 2 presents the values of objective functions calculated and the values for the set of corresponding parameters.

Table 2. Objective Functions Values

Parameters [$\rho; \eta; \mu; \lambda; \hat{\phi}(1)$]	Set	f_1	f_2
[0.8877;1.9888;0.0257;1.8762;2.0157]	DM	0.3889	0.4069
[0.6; 1; 1; 0.1; 2]	1	0.6882	0.9864
[0.6; 1; 1; 2; 2]	2	0.6078	0.6115

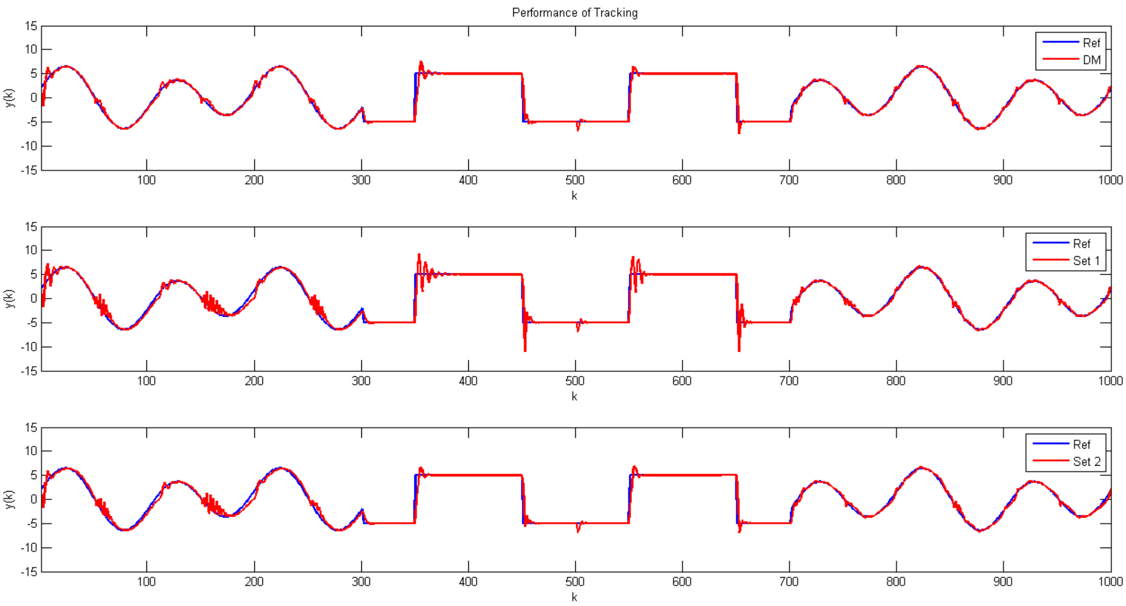

Figure 4. Graphics records of the reference signal and response of the controlled system using three set of parameters.

In both examples, the graphics records and the tables values shown that the controller with the optimized parameters had better performance than the one with parameters found in literature.

6 Conclusions

In this paper, we have studied an off-line tuning for parameters of a MFAC-CFDL controller and the initial value for estimated PPD of the system, for two examples, using a MODEA. The setting up of the parameters for MFAC is an open problem. To solve it, we used an evolutionary algorithm based on Multi-Objective Differential Evolution to get optimal parameters. In the method adopted, vectors of possible parameter values formed a population of solutions which evolves to eventually determine the Pareto front. The objective functions were chosen in order to reduce the error in the steady-state response and the maximum error of the transient period of the system. The closest point to the utopia one is chosen as a solution to set the controller parameters.

The results found by MODEA, in all examples, are Pareto better than other solutions presented in the literature. Additionally, the Pareto front, obtained at end of proposed strategy, provides the designer with a set of different solutions satisfying the control objectives at different levels of commitment between steady-state and transient errors. Despite the promising results, the solutions were obtained for the system off-line, using fixed initial conditions with the same reference signal. Therefore, there is no guarantee that the change in any of these conditions will make the controlled system behave optimally. An on-line strategy might be the solution to this problem, but on-line application to real-time control using multi-objective evolutionary algorithm is still rare at present (Reynoso-Meza et al, 2014).

As a future work, we consider propose new variations for the algorithm used, also study dynamical systems more complex for MFAC and try to develop a methodology for real-time problems.

References

Ali, M., Siarry, P., and Pant, M. (2012). An efficient differential evolution based algorithm for solving multi-objective optimization problems. European Journal of Operational Research, Vol. 217, pp. 404–416.

Abbass, H.A., Sarker, R., and Newton, C. (2001). PDE: A Pareto-frontier differential evolution approach for multi-objective optimization problems. In Proceedings of the 2001 Congress on Evolutionary Computation, Seoul, Vol.2, pp. 971–978.

Bu, X., Hou Z., and Chi, R. (2013). Model free adaptive Iterative learning control for farm vehicle path tracking. In Proceedings of the 3rd IFAC International Conference on Intelligent Control and Automation Science, Vol.46, No. 20, pp. 153-158.

Coello, C.A.C., Lamont, G.B., and Van Veldhuizen, D.A. (2007). Evolutionary Algorithms for Solving Multi-Objective Problems. 2º Ed, Springer, New York-NY .

Hou, Z. and Huang, W. (1997). The model-free learning adaptive control of a class of SISO nonlinear systems. In Proceedings of the 1997 American Control Conference, Albuquerque, Vol. 1, pp. 343–344.

Hou, Z. and Jin, S. (2011). Data-driven model-free adaptive control for a class of MIMO nonlinear discrete-time systems. IEEE Transactions on Neural Networks, Vol.22, No. 12, pp. 2173-2188.

Hou, Z. and Jin, S. (2014). Model Free Adaptive Control – Theory and Applications. 1º Ed, CRC Press, Boca Raton-FL.

Hou, Z.S. and Wang, Z. (2013). From model-based control to data-driven control: survey, classification and perspective. Information Sciences, Vol. 235, pp. 3–35.

Hou, Z. and Zhu, Y. (2013). Controller-dynamic-linearization-based model free adaptive control for discrete-time nonlinear systems. IEEE Transactions on Industrial Informatics, Vol.9, No. 4, pp. 2301- 2309.

Jalali, A., Piltan, F., Gavahian, A., Jalali, M., and Adibi, M. (2013). Model-free adaptive fuzzy sliding mode controller optimized by particle swarm for robot manipulator. I.J. Information Engineering and Electronic Business, Vol.1, pp. 68-78.

Ji, C., Wang, J., Cao, L., and Jin, Q. (2014). Parameters tuning of model free adaptive control based on minimum entropy. IEEE/CAA Journal of Automatica Sinica, Vol.1, No. 4, pp. 361-371.

Leng, Y., Li, H., Wang, P., and Qiao, Z. (2014). Model-free adaptive control with contractive constraints for nonlinear systems. In Proceedings of the 2014 Sixth International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Hangzhou, pp. 288-291.

Reynoso-Meza, G., García-Nieto, S., Sanchis, J., and Blasco, F. X. (2013). Controller tuning by means of multi-objective optimization algorithms: a global tuning framework. IEEE Transactions on Control Systems Technology, Vol.21, No. 2, pp. 445-458.

Reynoso-Meza, G., Blasco, X., Sanchis, J., and Martínez, M. (2014). Controller tuning using evolutionary multi-objective optimisation: Current trends and applications. Control Engineering Practice, Vol.28, pp. 58–73.

Roman, R.C., Radac, M.B., Precup, R.E., and Petriu, E.M. (2016). Data-driven model-free adaptive control tuned by virtual reference feedback tuning. Acta Polytechnica Hungarica, Vol.13, No. 1, pp. 83-96.

Sousa, J.T.G., Franca, J.E.M., and Araújo, A.F.R. (2015). Differential evolution-based parameter tuning in model-free adaptive control. In Proceedings of the 2015 IEEE International Conference on Systems, Man, and Cybernetics, Kowloon, pp. 1726-1731.

Xu, D., Jiang, B., and Shi, P. (2014). Adaptive observer based data-driven control for nonlinear discrete-time processes. IEEE Transactions on Automation Science and Engineering, Vol.11, No. 4, pp. 1037-1045.

Zhu, Y. and Hou, Z. (2014). Data-driven MFAC for a class of discrete-time nonlinear systems with RBFNN. IEEE Transactions on Neural Networks and Learning Systems, Vol.25, No. 5, pp. 1013-1020.