

Applications of multi-objective optimisation for PID-like controller tuning: a 2015-2019 review and analysis

Tainara Marques * Gilberto Reynoso-Meza *

* *Industrial and Systems Engineering Graduate Program (PPGEPS),
Pontifical Catholic University of Parana (PUCPR), Curitiba, PR,
Brazil (e-mail:tainara.marques@pucpr.edu.br;
g.reynosomeza@pucpr.br)*

Abstract: The first open invited track in multi-objective optimisation for control systems was organised in 2017 with the idea of exchanging ideas and research about how those techniques are valuable for control engineers. Given that control engineering problems are generally multi-objective problems, multi-objective optimisation offers an interesting approach via the simultaneous optimisation of all design objectives. Controller tuning is not except from this. In this paper we perform a review and analysis of the literature, limited to the IFAC environment, to appreciate and detect new tendencies in controller tuning applications via multi-objective optimisation. Time window under consideration is from 2015 to date, coinciding with a previous review on the topic, as well as the emigration of IFAC proceedings to Elsevier.

Keywords: Multi-objective optimisation, Parametric optimisation, Evolutionary Algorithms, Intelligent Control, Process Control.

1 Introduction

Control engineering problems are generally multi-objective problems; which means that there are several specifications and requirements that must be fulfilled, often in conflict. A traditional approach for calculating a solution with a desired trade-off is defining an optimisation statement. Multi-objective optimisation techniques deal with such a problem from a particular perspective by searching for a set of potentially preferable solutions: the so called Pareto set. The designer may then analyse the trade-off among solutions in this set, and select the most preferable alternative according to the problem at hand. Controller tuning can be considered as a multi-objective problem, given that a set of requirements and specifications must be fulfilled. In this sense, multi-objective optimisation techniques have shown to be valuable tools for this task (Reynoso-Meza et al., 2014, 2016b).

In this paper, we perform a systematic review of literature, to identify papers where the multi-objective optimisation approach has been used. This follow a previous review (Reynoso-Meza et al., 2014), but focusing on PID-like controllers and also following the first version of this open invited track. Major aim of this paper is to track multi-objective optimisation ideas for controller tuning, presented in IFAC conferences, and their evolution to an IFAC journal. This with the purpose of performing

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a critical analysis on how multi-objective techniques are being received in the control community (limited to the IFAC environment).

The remainder of this paper is as follows: in Section 2 a brief background on multi-objective optimisation techniques is given; In Section 3 some comments on the controller tuning as a multi-objective optimisation problem is given. In Section 4 conference and journal papers matching our search criteria are commented. Finally some discussion and conclusions are derived from this review.

2 Multi-objective optimisation design procedure

Roughly speaking, multi-objective optimisation techniques seek a better solution to a mathematical problem with more than one design objective, via a simultaneous approach. Multi-objective problems can be defined, in general, as follow:

$$\min_{\theta} J(\theta) = [J_1(\theta), \dots, J_m(\theta)] \quad (1)$$

subject to:

$$g(\theta) \leq 0 \quad (2)$$

$$h(\theta) = 0 \quad (3)$$

$$\underline{\theta}_i \leq \theta_i \leq \bar{\theta}_i, i = [1, \dots, n] \quad (4)$$

where $\theta \in \mathfrak{R}$ is the decision vector, $J(\theta)$ is the objective vector, $g(\theta)$ and $h(\theta)$ are, respectively, the inequality and equality vectors, lastly, $\underline{\theta}_i \leq \theta_i \leq \bar{\theta}_i$ being the research dimension for the decision space for the variable θ (Miettinen, 1999).

It is noted that there is not a better solution for all objectives, since the improvement of one objective can worsen a second one. Therefore, a set of solutions classified as Pareto set is defined (Marler and Arora, 2004); each solution of this set defines an objective vector in the Pareto front (See Figure 1). All the solutions presented in Pareto front are considered to be a set of Pareto-optimal and non-dominated solutions:

- **Pareto optimality** (Miettinen, 1999): An objective vector $J(\theta^1)$ is Pareto optimal if there is no other objective $J(\theta^2)$, such that, $J_i(\theta^2) \leq J_i(\theta^1)$ for all $i \in [1, 2, \dots, n]$ and $J_j(\theta^2) < J_j(\theta^1)$ for at least one $j, j \in [1, 2, \dots, n]$.
- **Dominance** (Coello and Lamont, 2004): An objective vector $J(\theta^1)$ is dominated by another objective vector $J(\theta^2)$ iff $J_i(\theta^2) \leq J_i(\theta^1)$ for all $i \in [1, 2, \dots, n]$ and $J_j(\theta^2) < J_j(\theta^1)$ for at least $j, j \in [1, 2, \dots, n]$. This is denoted as $J(\theta^2) \preceq J(\theta^1)$.

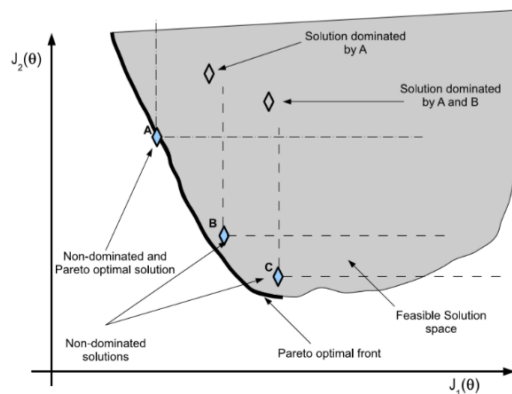


Fig. 1. Pareto optimality and dominance concepts. Source: Meza et al. (2016).

Three fundamental steps are required for a correct implementation of the multi-objective approach; these steps are: multi-objective problem definition (MOP), multi-objective optimisation (MOO) process and the multi-criteria decision making (MCDM) stage. From now on this integral and holistic procedure will be denoted as a multi-objective optimisation design procedure (MOOD) Meza et al. (2016).

2.1 Multi-objective problem statement

According to Mattson and Messac (2005), at this stage the following must be defined: the design concept (how to solve the problem in question); engineering requirements (which is important to optimise); and constraints (which solutions are not practical/permitted).

2.2 Multi-objective optimisation process

Different from single objective optimisation, where an aggregation function is used to merge all design objectives, in multi-objective optimisation a simultaneous approach is used, with the aim of approximating a Pareto front. Evolutionary and bio-inspired algorithms as Genetic Algorithms (GAs), Particle Swarm Optimisation (PSO) and Differential Evolution (DE) has been used with success.

Independently of the optimisation paradigm used, the following three concepts are fundamental in the Pareto front approximation (and normally used to measure its quality):

- **Convergence (conv):** As can be seen in the Figure 2, convergence refers to the ability of the algorithm to find values on the real Pareto front, usually this front is unknown.
- **Diversity (div):** A diversity mechanism algorithm is able to obtain a set of distributed solutions in Pareto front, providing a useful description between conflicting objectives and decision variables, as it can be noticed in Figure 3.
- **Pertinency (per):** Pertinency (Figure 4) refers to the algorithm's capacity to reach solutions that are interesting to the decision maker in his/her point of view.

Regarding the optimisation statement, in controller tuning is common to find the following two instances:

- **Constrained optimisation:** It serves to limit the search space in the optimisation problem, but also to guarantee feasibility and practicality of a given solution.
- **Many-objectives optimisation:** Refers to problems with typically more than five objectives to be optimised simultaneously (Corne and Knowles, 2007). A comparative study between many-objective evolutionary optimisation techniques is presented in Li et al. (2018).

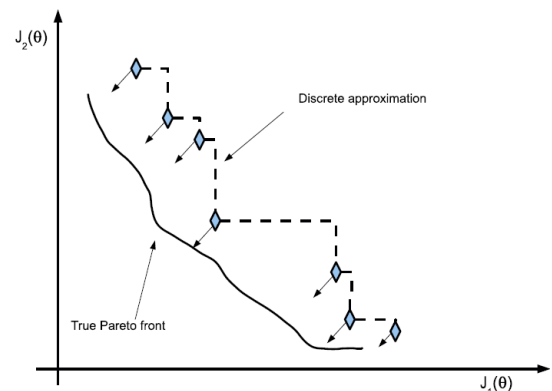


Fig. 2. Convergence concept. Source: Reynoso-Meza et al. (2014)

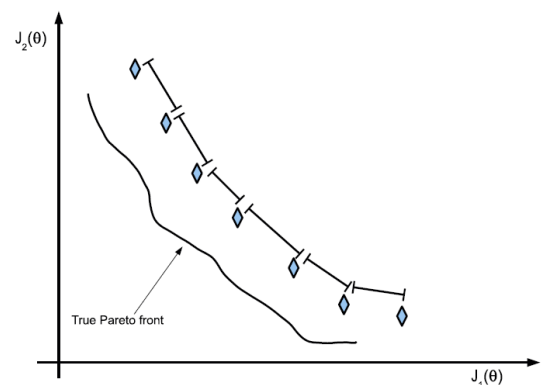


Fig. 3. Diversity concept. Source: Reynoso-Meza et al. (2014)

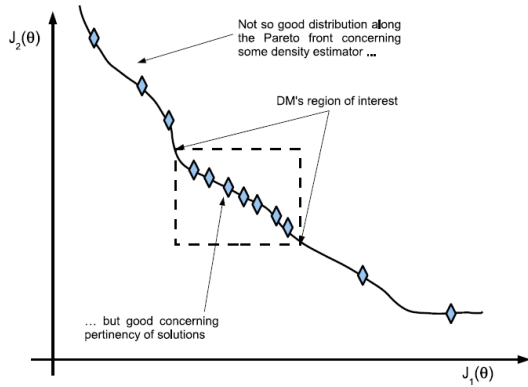


Fig. 4. Pertinency concept. Source: Reynoso-Meza et al. (2014)

2.3 Multi-criteria decision making

After the multi-objective optimisation process, the decision maker now needs to analyse the trade-off between the conflicting objectives of the Pareto front approximation to select the most preferable solution according to their preference. In order to improve the interpretability on the the relationships between design objectives it is common to employ different multi-dimensional visualisation techniques (Tušar and Filipič (2015)).

3 Controller tuning as a multi-objective optimisation design procedure

We will focus on proportional-integral-derivative (PID) controllers, given that they remain as a trustful and common solution to a wide variety of control problems (Samad, 2017). A two degree of freedom PID controller with derivative filter $C(s)$ can be parameterized in terms of proportional gain k_p , integral time T_i , and derivative time T_d as follows:

$$C(s) = k_p \left(a + \frac{1}{T_i s} + b \frac{T_d}{\frac{T_d}{N} s + 1} \right) R(s) - k_p \left(1 + \frac{1}{T_i s} + \frac{T_d}{\frac{T_d}{N} s + 1} \right) Y(s) \quad (5)$$

where a and b are the set point for proportional and derivative action respectively, N the derivative filter, $R(s)$ the reference, and $Y(s)$ the measured signal. Thereby, the decision variables can be declared, using the nomenclature suggests by Reynoso-Meza et al. (2014), in the following way:

$$\begin{aligned} PI : & \quad \theta_{PI} = [k_p, T_i] \\ PD : & \quad \theta_{PD} = [k_p, T_d] \\ PID : & \quad \theta_{PID} = [k_p, T_i, T_d] \\ PID/N : & \quad \theta_{PID/N} = [k_p, T_i, T_d, N] \\ PI^1 : & \quad \theta_{PI^1} = [k_p, T_i, a] \\ PID^2 : & \quad \theta_{PID^2} = [k_p, T_i, T_d, a, b] \\ PID^2/N : & \quad \theta_{PID^2/N} = [k_p, T_i, T_d, N, a, b] \end{aligned} \quad (6)$$

Also, common design objectives to evaluate its performance and/or robustness are:

- Maximum value of sensitivity function: $J_{M_s}(\theta) = \|(I + P(s)C(s))^{-1}\|_{\infty}$ (7)
- Disturbance attenuation performance: $J_{w_1}(\theta) = \|W(s)(I + P(s)C(s))^{-1}\|_{\infty} < 1$ (8)
- Maximum value of the complementary sensitivity function: $J_{M_p} = \|P(s)C(s)(I + P(s)C(s))^{-1}\|_{\infty}$ (9)
- Robust stability performance: $J_{W_2} = \|W(s)(P(s)C(s))(I + P(s)C(s))^{-1}\|_{\infty} < 1$ (10)

- Integral of the absolute error value:

$$J_{IAE} = \int_{t=t_0}^{T_f} |r(t) - y(t)| dt \quad (11)$$

- Integral of the time weighted absolute error value:

$$J_{ITAE} = \int_{t=t_0}^{T_f} t|r(t) - y(t)| dt \quad (12)$$

- Integral of the squared error value:

$$J_{ISE} = \int_{t=t_0}^{T_f} (r(t) - y(t))^2 dt \quad (13)$$

- Integral of the time weighted squared value:

$$J_{ITSE} = \int_{t=t_0}^{T_f} t(r(t) - y(t))^2 dt \quad (14)$$

- Integral of the square of the control action value:

$$J_{ISU} = \int_{t=t_0}^{T_f} (u(t))^2 dt \quad (15)$$

- Total variation of the control action:

$$J_{tv} = \int_{t=t_0}^{T_f} \left| \frac{du}{dt} \right| dt \quad (16)$$

- Maximum value of control action:

$$J_{maxU} = \max(u(t)), t \in [t_0, T_f] \quad (17)$$

- Settling time:

$$J_{St(100-\Delta)\%}(\theta) \quad (18)$$

- Overshoot:

$$J_{over}(\theta) = \max \left[\max \left(\frac{y(t) - r(t)}{r(t)} \right), 0 \right], t \in [t_0, t_f] \quad (19)$$

Having raised the background about multi-objective optimisation techniques and PID-like controllers, we will present next IFAC papers who used these techniques for controller tuning purposes.

4 Literature review

This review follows a previous review on the area (Reynoso-Meza et al., 2014). Search and selection criteria are as follows:

Table 1. Summary of papers matching search and selection criteria.

Reference	Process(es)	Concept(s)	MOP			MOO	Algorithm Basis	Related features from Section 2	Plot	MCDM
			$J(\theta)$	θ	$(g(\theta), h(\theta))$					
Moarref et al. (2016)	Voltage and frequency regulation; MIMO	PI	4	2	(2,0)	MOHBB-BC	Conv; Div	3D	Fuzzy	
Velasco Carrau et al. (2017)	Unmanned aerial vehicle; MIMO; Cascade	PI	9	10	(10,0)	DE	Conv; Div; Per	2D; LD	Hil	
Porru and Özkan (2019)	Crystallization processes; SISO	PI	3	4	(3,2)	Patternsearch		Table	Comparing the results	
Kumar et al. (2018)	MIMO	FO $PI^\lambda D^\mu$	3	8	(6,0)	GA	Div	2D	Designer choose the best solution	
Prabakar and Li (2015)	Power system; SISO	PI	4	2	(2,0)	GA	Conv; Div	2D	user needs from the system	
Reynoso-Meza and Sánchez (2018)	SISO	PI	3	4	(1,0)	DE	Div	3D; SCp; LD	According to a given norm or measure	
Reynoso-Meza et al. (2018)	Refrigeration; MIMO	PI	5	6	(4,0)	DE	Div; Per	SCp	Preference matrix	
Gamboa et al. (2017)	Industrial process; SISO	2DoF PID	3	4	(1,0)	ENNC		Table	Level of robustness given	
Reynoso-Meza et al. (2016a)	SISO	PID	3	3	(6,0)	DE	Div; Per	LD	Trade-off analysis	
Gambier and Behera (2018)	Wind turbine; MIMO	PI	3	7	(9,0)	PSO		2D	Compromise Solution	
Ayala et al. (2017)	Distillation column; MIMO	Decentralized PID	3	4	(1,0)	MOHKA	Conv; Div	2D; LD	Decision maker preference	
Herrero et al. (2017)	MIMO	2DOF-PID	2	8	(10,0)	GA		2D	closest to the ideal point	
Denisova and Meshcheryakov (2016)	Automatic control system; MIMO	PI	2	2	(0,0)	GA	Conv; Div	2D	Analysis the number of pulses	
Fu et al. (2017)	Thermal; SISO	cascade PI	2	2	(1,0)	PSO		2D	Selection according to preferences	
Pandit and Hingu (2018)	Diesel Engine; SISO	PID	4	4	(0,0)	Ad-hoc		SCp		
Gambier (2019)	Wind turbine; MIMO;	PID	2	6	(3,0)	PSO		2D	Bargaining criteria	

- Time window: 2015-2019, coinciding with the last review (2014) and the emigration of IFAC proceedings to Elsevier.
- Sources : IFAC conferences (*IFAC Papers on line*) and IFAC paper journals (*Automatica, Control Engineering Practice, Annual Reviews in Control, Engineering Applications of Artificial Intelligence, Journal of Process Control, Mechatronics, Nonlinear Analysis: Hybrid Systems, IFAC Journal of Systems and Control*).
- Keywords : Multi objective; optimisation; controller; front.
- Exclusion criteria : absence of a Pareto front approximation.

Next, papers within search criteria and a brief description on their contents will be commented. In Table 1 a summary is shown. Regarding conference papers, via *IFAC papers on*

line it is possible to find ten papers dating from 2015 to date, fitting the search criteria. In Prabakar and Li (2015) a GA based in MOO was placed to optimise the K_p and K_i of a PI controller for a power system. Four objectives were defined to quantify the performance of the controller. They are rise time, overshoot, peak response and settling time. The best solution was chosen according to the user needs from the system.

Reynoso-Meza et al. (2016a) proposes the adjustment of a PID controller for an unstable first order plus dead time (UFOPDT) process. The sp-MODE algorithm was used to optimise the decision variables K_p , T_i and T_d , with the objectives related to performance, setting time, and robustness, with gain and margin phase. The level diagram is used to visualise and analyse the Pareto front.

In 2017, from the international IFAC conference and the previous version of this open invited track, four papers match the criteria: in Herrero et al. (2017) was studied a new multi-objective approach for loop pairing in multiple-input multiple-output (MIMO) processes with a 2DOF-PID control. Three approaches are suggested and compared to select the best approach. The Pareto-optimal solution with the shortest Euclidean distance to the utopian point was chosen between the decision variables K_p , T_i , T_d and b for the 2DOF PID concept, optimised by GA technique. The objectives took into account the effort and performance of the controller in question. The authors establish that analysing the input-output pairing using a multi-objective approach is a powerful and promising technique.

A new heuristic algorithm for multi-objective optimisation based on Kalman filtering is exposed in Ayala et al. (2017). This new approach is tested using the Wood and Berry distillation column model using a decentralised PI controller. The decision variables are K_p and T_i ; the objective functions aim to evaluate the performance and robustness of the controller, minimising the integral gain and biggest log modulus. The performance is compared with NSGA-II and proved to be favourable.

Apart of the open track, in Gamboa et al. (2017) was introduced a toolbox for multi-objective optimisation and its parameters selection for PID² controllers. To use this tool, the user must to inform a plant model, a desired robustness and the allowed degradation of each cost function. A MOP is stated with decision variables K_p, T_i, T_d and b and three objective functions based on the IAE index; the Enhanced Normalised Normal Constraint (ENNC) was selected for the MOO process. At the end, the tool provides the Pareto-optimal solution, which is chosen as a trade-off between robustness and time response simulation of the closed-loop performance;

Finally multi-objective techniques are applied to tune the inner-loop and outer-loop of a superheated steam temperature power plant with a cascaded PI controller in (Fu et al., 2017). The applied optimisation technique is MOPSO with two design objectives based on the IAE index; one to represent the performance index for a set-point tracking and other for disturbance rejection. The author optimised the controller with and without considering the robustness constraint, revealing that the results can be misleading when robustness is not considered.

In 2018 the following works were presented: a control strategy was proposed for the excitation system of a synchronous generator in Kumar et al. (2018). Design objectives in time and frequency domain are used to escalate the robust stability, minimise the error and the energy consumption. The MOO process is solved by using a generic algorithm to find the design parameters related to the fractional order (FO) $PI^\lambda D^\mu$ controller; the excitation system, voltage measurement unit and power amplifier module, allows the designer to select a particular controller configuration. This paper reached good solutions to the problem improving the dynamic robust stability with minimum energy consumption.

In Reynoso-Meza and Sánchez (2018) were compared different multidisciplinary optimisation approaches using multi-objective techniques. Two decision variables are related with the dynamic of the plant and two (K_p, K_i) with control tuning. Such decision variables are optimised simultaneously to evaluate synergies between plant design and control parameters. Two different MOPS are stated: the first one with design objectives ITAE, IAE and robustness; the second one with design objectives settling time, overshoot and robustness.

In Reynoso-Meza et al. (2018) a controller for a cooling system benchmark using MOOD techniques was presented. In the MOP statement, a decision vector with 6 decision variables related to controller parameters and five design objectives to measure performance and robustness are proposed. The sp-MODEx is used to approach the Pareto front and Pareto set. The resulting controller meets the requirements of the contest in which the article was participating and outperformed the base line controller.

(Pandit and Hingu, 2018) suggests a black box methodology for the online adjustment of a controller for the Cummins engine. The hybrid algorithm based on PSO and GA was designed and used to find values of K_p, K_i, K_d and N , configured to obtain better performance indexes between rise time, settle time, overshoot and steady state error. In the end, the proposed algorithm obtained a result superior to GA with a number significantly less than steps.

Finally in Gambier and Behera (2018) a controller was tuned for the pitch control system of a large-sized wind turbine. The author presents an integrated pitch control system, which consists of three control circuits. The optimisation process is configured by seven decision variables linked to the gains of PI controllers and the objective functions are based on the ITSE for each control circuit. Using a MOPSO optimisation algorithm, the simulation results showed satisfactory performance for all control loops.

In Gambier (2019) a evolutionary multi-objective optimisation with fractional order objective functions is used to tune the same system presented in (Gambier and Behera, 2018). With the new control structure, the multi-objective optimisation process now has six decision variables and two objective functions. The Kalai-Smorodinsky solution (KS) is accepted as best solution for the problem. This point is situated at the intersection of the Pareto front and the straight line between the threat point and the utopia point.

Regarding journal papers, it is possible to find papers matching our search criteria in *Engineering Applications of Artificial Intelligence* (EAAI), *Journal of Process Control* (JPC) and *Control Engineering Practice* (CEP). In CEP we find the work of Moarref et al. (2016) where the multi-objective technique is applied to find the gains for a voltage and frequency regulator. The MOP was formulated using as objective functions the voltage overshoot/undershoot, rise time, settling time, and the ITAE criteria. The Proportional-Integral (PI) gains are optimised in real-time by The modified Multi-Objective Hybrid Big Bang-Bing Crunch (MOHBB-BC) algorithm (MOHBB-BC). To select the final solution a fuzzy decision maker is used, the

proposed method got a more appropriate response than previous works.

In EAAI it is possible to find a paper on the integration of multi-objective optimisation techniques and Hardware in the loop tests (Velasco Carrau et al., 2017). In order to solve the control problem, this paper presented a methodology where multi-objective optimisation and multi-criteria decision making steps are sequentially performed over the platforms *Model in the Loop* (MiL), *Software in the Loop* (SiL) and *Processor in the Loop* (PiL). Thereby, as the optimisation stage progresses between platforms, the complexity of the problem is revealed to the designer, allowing to declare significant design objectives.

Finally JPC the work of (Porru and Özkan, 2019), handles which design and control of crystallisation processes together. Therefore, the conflicting objectives have been optimised simultaneously, in order to solve the problem between process economics, product quality criteria as well as process controllability. The crystallises configuration with the best trade off between the objectives. With this, the simultaneous design and control are completed adapting a controller to the ideal configuration.

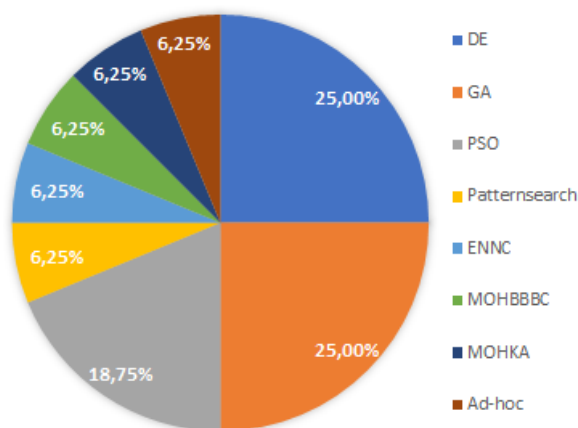


Fig. 5. Pie chart on the algorithms presented in Table 1.

For a better understanding on the algorithms used in the MOO process, a pie chart is depicted in Figure 5. It is possible to notice that GA and DE algorithms are mainly used for this purpose.

Design objectives used functions are ordered in Table 2. With this we notice that there is no preferred goal between the author duo the diversity of objective applied. Some of them were used more than others, are the case of IAE, settling time and overshoot.

5 Discussion and conclusions

As already commented, in Table 1 a summary of the papers matching the search and selection criteria is presented. In such table we are collecting information regarding the process under study; if it is single-input single-output (SISO) or MIMO; controller tuned; quantity of design objectives, decision variables and constraints; algorithm type and features commented in Section 2 about the MOP statement; visualisation and decision making insights are also included.

First thing interesting to note is that from 16 papers, just three of them appeared in an IFAC journal. Therefore, it is interesting to think over why those techniques are more willing to appear in IFAC-conferences instead of IFAC-journals.

About the MOP statement, it was commented by Reynoso-Meza et al. (2014) that few works consider decision variables such N , a , b as integral parts of the PID tuning procedure. With this review the same tendency apply, given that just three papers (Gamboa et al., 2017), (Herrero et al., 2017) and (Pandit and Hingu, 2018)) remarked on the importance of using those decision variables; in Gambier and Behera (2018); Gambier (2019) those variables are used with constant values. When compared with the previous review, more works are focusing in multivariable processes (9 papers). Pertinency seems to be again, a feature to be exploited in multi-objective optimisation while constrained optimisation seems to be more assimilated in the MOP statement.

Next fact to note is that, although GA algorithms continue to be widely used, there has been an expressive growth in the use of DE. Tendency also is to use evolutionary algorithms, and using as basis well established techniques (we can count just 3 new algorithms). In the MCDM stage, 2D representation using scatter plots continue to be the more popular method to analyse trade-off.

It is planned to continue with this review, with the full spectrum of multi-objective optimisation approaches for tuning, modelling and/or sensing. Also to track effectively if any conference idea evolves to journal papers, outside the IFAC environment.

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Table 2. Summary of design objectives used in the commented papers.

Reference	Ms	IAE	$ITAEISE$	$ITSEISU$	tv	St	$over$	Others
1 Moarref et al. (2016)			x			x	x	Rise time
2 Velasco Carrau et al. (2017)					x			Time required to perform a flight and number of successful flight
3 Porru and Özkan (2019)								Economic and Quality criteria
4 Kumar et al. (2018)	x		x					∞ -norm
5 Prabakar and Li (2015)						x	x	Peak response and Rise time
6 Reynoso-Meza and Sánchez (2018)	x	x	x			x	x	
7 Reynoso-Meza et al. (2018)		x			x			
8 Gamboa et al. (2017)		x						
9 Reynoso-Meza et al. (2016a)						x		Gain and phase margin
10 Gambier and Behera (2018)				x				
11 Ayala et al. (2017)								Integral gain and Biggest log modulus
12 Herrero et al. (2017)			x	x	x			
13 Denisova and Meshcheryakov (2016)			x	x				
14 Fu et al. (2017)		x						
15 Pandit and Hingu (2018)						x	x	Steady state error and Rise time
16 Gambier (2019)				x				

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