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Professional paper

An approach to tune Controller parameters via Bio-inspired evolutionary optimization strategy (μ + λ)

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Abstract

In this paper, we are describing an approach that can be used to solve modern control engineering problems. Controller parameters tuning is an important problem in control engineering. In industry, for optimum solutions, Proportional-Integral-Derivative (PID) controllers, have been widely used. Therefore, PID parameters optimization is an important problem in Control Systems Engineering. Tuning the controller based on an Evolutionary Strategy-ES $(\mu + \lambda)$, based on a criterion defined using an objective function, helps the optimal calculation of the PID controller parameters which leads to a high level of accuracy and system performance. This method converges to an optimal solution that gives us the minimum error. The designed PID with ES $(\mu + \lambda)$ has a fast response and gives us great results in terms of the rise time, settling time, overshoot and steady state error. Evolutionary Strategies (ES) are most commonly used to black box optimization problems in continuous search spaces inspired by biological evolution, particularly based on the Darwinian evolution. Their original formulation is based on the imitation of the nature and application of genetic operators such as mutation, recombination and selection in populations of candidate solutions. The case study confirms that great performance of the system can be achieved by the proposed method.

Keywords: Controller tuning; PID; Evolutionary algorithms; Optimization; AI.

Introduction

Since in industry the PID controller is being largely used, tuning methods and procedures for PID controllers are always of high importance. The main objective of this work is to use the evolutionary strategy $(\mu + \lambda)$ in the process of tuning the PID controllers. The algorithm searches for the controller gains K_P(proportional gain), K_i(integral gain) and K_d(derivative gain) so that specifications for the closed-loop step response are fulfilled.
Evolutionary strategies (ES) are inspired by biological evolution, particularly based on the Darwinian evolution. Their original formulation is based on the imitation of the nature and application of genetic operators such as mutation, recombination and selection in populations of candidate solutions.
In the following sections concepts and modeling of PID controllers via evolutionary strategy $(\mu + \lambda)$ are presented. Also this method is going to be tested by tuning the PID controller for a

mechatronic system. The optimization objectives will be defined by the objective function. This method searches for an optimal solution that gives us the minimum error.

PID controller

Mostly the PID is used as a controller in industrial systems, when a closed loop system control is used. The PID controller has three gains, the proportional gain (K_P), the derivative gain (K_d) and the integral gain (K_i) [5].
The error $e(t)$is the difference between the set-point and the output of the plant. The controller acts by correcting the error in the system, and therefore will adjust the plant output.
The proportional part is responsible to follow the desired set-point, while the integral part account for the accumulation of past errors and derivative accounts for the rate of change of error in the process [10].
The general form of the PID controller is:

$$g_c(t) = K_P e(t) + K_i \int_0^t e(t)dt + K_d \frac{de(t)}{dt} \quad (1)$$

In the Laplace domain the aforementioned equation for the PID controller is given as follows:

$$G_c(s) = K_P + K_i \frac{1}{s} + K_d s \quad (2)$$

These three parameters of the PID controller can be tuned based on bio-inspired evolutionary strategy optimization technique, respectively the evolutionary strategy$(\mu + \lambda)$. The optimization leads to the desired performance depending on the requirements of the system specified by the objective function.

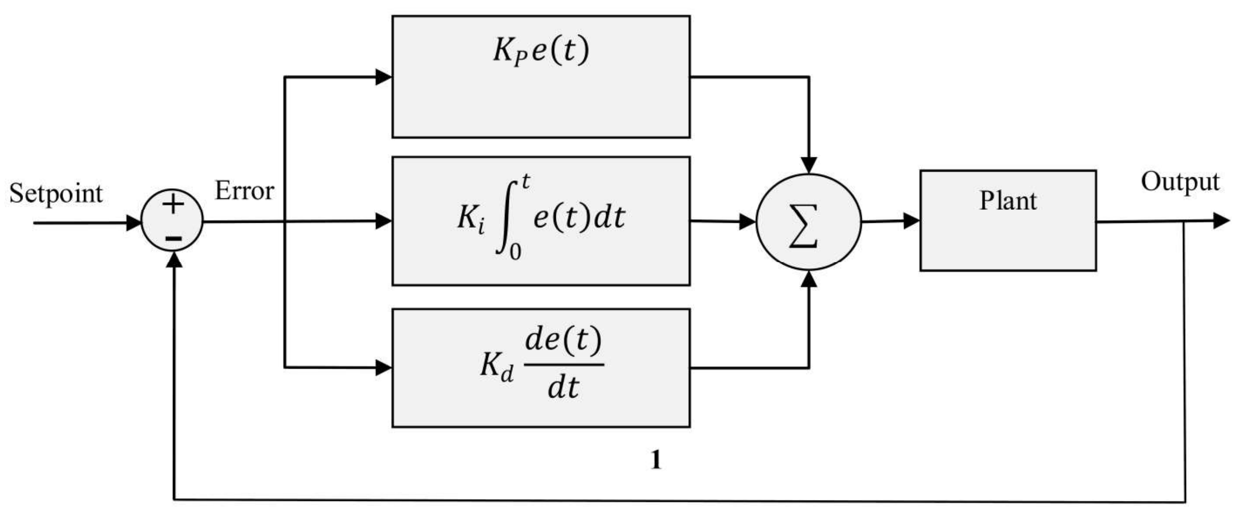


Figure 1. Block diagram of the PID controller

The mechatronic system

In order to demonstrate the effectiveness of this approach we are going to try the algorithm by tuning the PID controller parameters for a mechatronic system. The mechatronic system consists of an electrical system, rotating part of the mechanical system and the mechanical translation part at the end. This model is composed of all the necessary components to be considered for a mechatronic system. From the control perspective we have to design a motion control system which is required to provide a motion control with a precise end motion [1].

The mathematical model (the transfer function in the Laplace domain) for the mechatronic system is [1]:

$$Transfer\ function\ = \frac{0.0571}{s^2 + 0.6s + 0.3432} \tag{3}$$

Objective function

To determine a suitable controller for our system, we have to define an objective function. The objective function (fitness function) describes how the controller reacts to disturbances (load changes). Objective function is used to determine whether a chromosome is a good solution to our problem. Each chromosome has its own fitness value by calculating the fitness function. And the chromosome which is the fittest will survive. In order to get great results, the fitness function should be properly defined, otherwise we get poor solution even when the fitness value is fitted.

There are different objective functions that have been written based on error performance criterion. In principle, each fitness function is same except the part where we define the error performance criterion which is being implemented. In our case we have implemented the integral of time multiplied by absolute error (ITAE).

The ITAE weights the error with time and hence emphasizes the error values later on in the response rather than the initial large errors [6].

When we optimize the performance of a PID controlled system, the PID parameters of the system are adjusted to maximize or minimize a specific performance index. Over a time interval the performance index is calculated; T, is in the region of $0 \leq T \leq t$where t is the system's settling time [6]. The time t that multiplies the absolute error penalizes later errors.

The integral time absolute error (ITAE):

$$I_{ITAE} = \int_{o}^{T} t|e(t)|dt \tag{4}$$

The integral of time multiplied by absolute error (ITAE) is usually used in optimal analysis and design. In our case, we obtain the maximum fitness values using the evolutionary strategy ($\mu + \lambda$) to find the best chromosomes (fittest). However, when the problem is to find the minimum value instead of the maximum value, then we have to transform a minimization problem to a maximization problem [9]. Because we need to minimize the error. The fitness function is taken as inverse of error, respectively performance index, since the smaller the value of performance indices of the corresponding chromosomes the fitter the chromosomes are going to be, and vice versa. Therefore, we define our fitness function as follows:

$$Fitness\ function = \frac{1}{performance\ index} = \frac{1}{ITAE} = \frac{1}{\int_o^T t|e(t)|dt} \quad (5)$$

```
delt = 0.01;

t = 0:delt:1;


%The error

error = 1 - step(feedback(plant*PID,1), t);
```

Figure 2. *Objective function with ITAE*

Evolutionary strategy $(\boldsymbol{\mu} + \boldsymbol{\lambda})$

The objective of the evolutionary strategies is optimization of objective functions(s) $\boldsymbol{F}$ with respect to a group of variables known as objective parameters $\boldsymbol{y} \coloneqq (\boldsymbol{y_1}, \boldsymbol{y_2}, \boldsymbol{y_3}, \ldots)$. Let us consider the following objective function $\boldsymbol{F}(\boldsymbol{y}), \boldsymbol{F} \in \boldsymbol{\mathcal{F}}$,as optimization problem [3].

$$\boldsymbol{F}(\boldsymbol{y}) \to \boldsymbol{opt.}, \quad \boldsymbol{y} \in \boldsymbol{\mathcal{Y}}.$$

In general, $\mathbf{y}$ could be a finite value but not necessarily of a fixed length. For instance $\boldsymbol{\mathcal{Y}}$ can be real values in the N-dimensional search space $\mathbb{R}^{\boldsymbol{N}}$, search space of integer numbers $\mathbb{Z}^{\boldsymbol{N}}$, binary search space $\mathbb{P}^{\boldsymbol{N}}$, or combination of these search spaces.
Evolutionary strategies (ES) were invented by Rechenber, Schwefel that operates with populations of size $(\mu + \lambda)$[3].

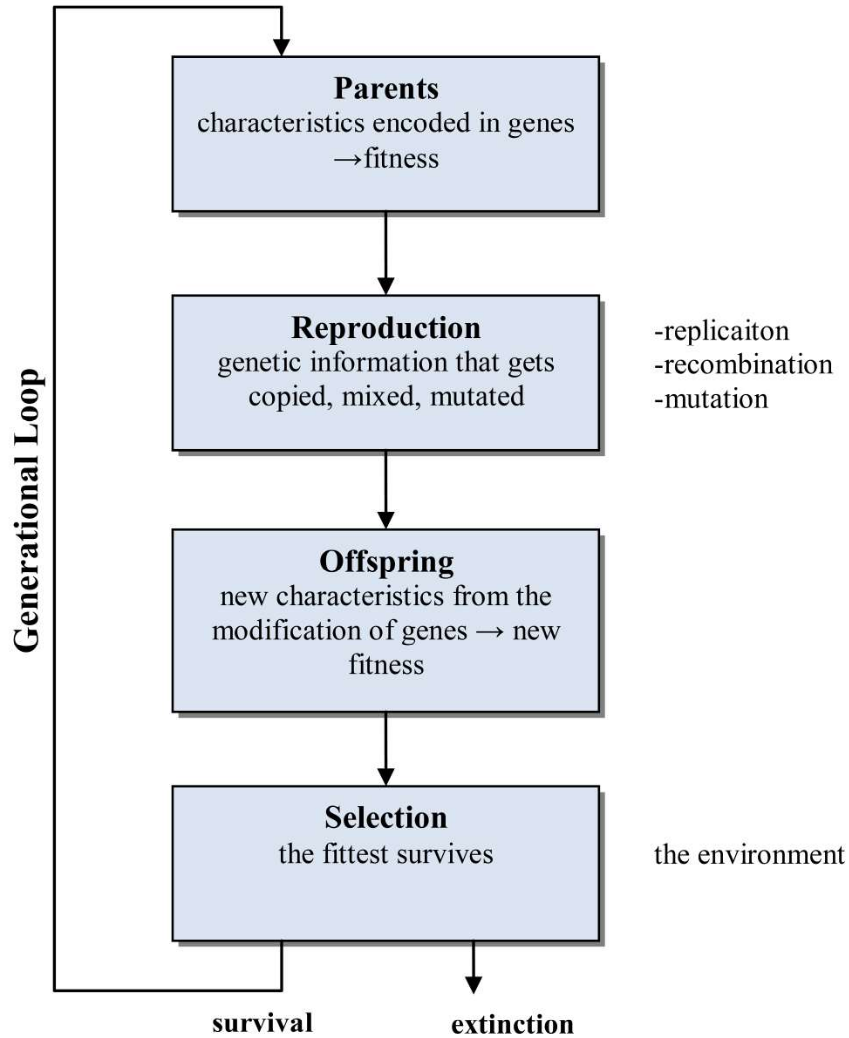


Figure 3. The evolutionary algorithm

Evolutionary strategy $(\mu + \lambda)$pseudo-code [4]:

1 population μ = random
2 fitness = evaluate (population)
3 mutants λ = mutate (population)
4 fitness’ = evaluate (mutants)
5 population = best of (population + mutants)
6 if not stop, go to 3

Structure and design of ES ($\boldsymbol{\mu + \lambda}$) based PID controller

The structure of a control system with ES ($\mu + \lambda$)-PID as a controller consists of a conventional PID controller with its parameters optimized by evolutionary strategy ($\mu + \lambda$). The structure of the control system is shown in the following figure.

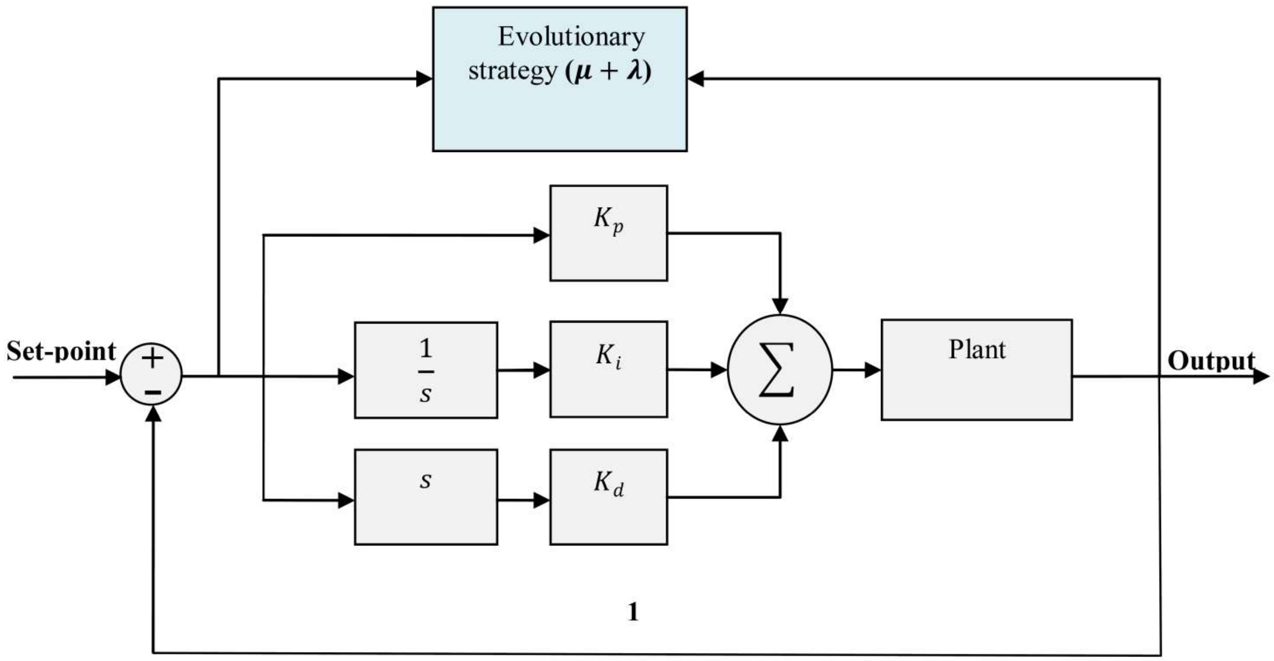


Figure 4. Structure of ES ($\mu + \lambda$)-PID controller

Evolutionary strategy ($\mu + \lambda$) searches for maximum fitness.

The input arguments are [4]:
- objective function - name of the objective function, returns the fitness of particular solution.
- chromosome length - number of genes (variables) in a chromosome.
- population size - ($\boldsymbol{\mu}$) number of individuals in population (at least 1).
- offspring size - ($\boldsymbol{\lambda}$) size of offspring population (at least "$\boldsymbol{\mu}$").
- stopping criteria - maximal number of iterations.

With the evolutionary algorithm ($\mu + \lambda$) we determine the values of the three parameters of the PID controller. When we implement the tuning procedure via evolutionary strategy ($\mu + \lambda$) we start by defining the chromosome. As illustrated in Figure 5, the chromosome is formed by three values that correspond to the three gains that have to be adjusted in order to get optimal solution, particularly a satisfactory behavior of the system. Therefore, the number of genes in a chromosome is the number of variables that need to be optimized. Here an analogy with biology can be made where every gene represents a feature of something. In our case each parameter of the controller has its own responsibility for the system, and could affect the system differently. Thereby optimizing these parameters gives as an optimal solution for the system.

K_p	K_i	K_d

Figure 5. Defined chromosome

Initialization of the Evolutionary strategy ($\mu + \lambda$)

For this case study we have used the following values.

```
% Delete previous data
delete data.matpopulation*.matoffspring*.mat


% Run the algorithm
chromosome_length = 3;  % three real variables (Kp, Kd, Ki)
```

Figure 6. Initialization of the evolutionary strategy ($\mu + \lambda$)

Results from the evolutionary strategy

With the evolutionary strategy ($\mu + \lambda$) we determine the values for the parameters of the PID controller. These parameters represent genes of the chromosome (number of the variables in a chromosome).

After the execution of the evolutionary strategy ($\mu + \lambda$) with a stoping criteria at 500 iterations, we get the following parameters for the PID controller: ***Kp* =257.9508*; Kd* =421.4386*; Ki* =138.7718.**

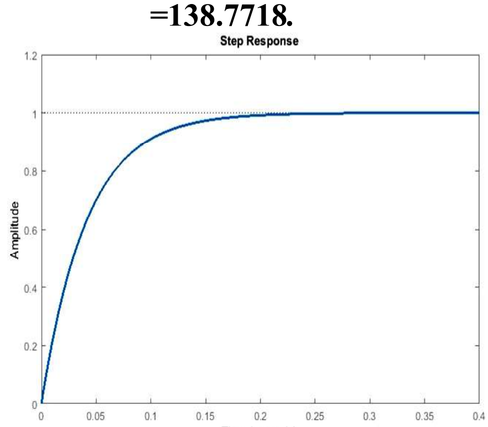
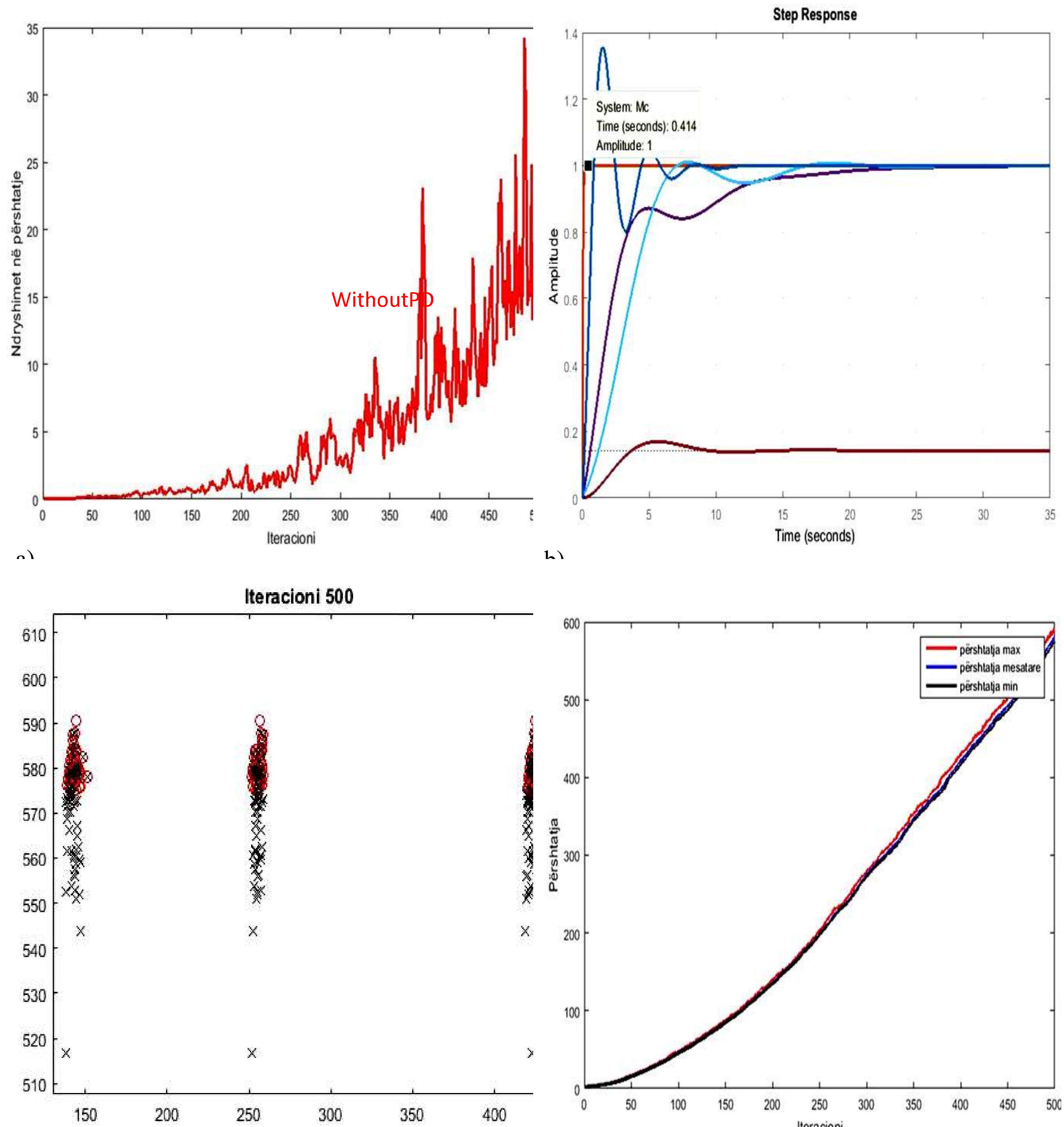


Figure 7. The response of the system with *Kp* =257.9508*; Kd* =421.4386*; Ki* =138.7718



c)

Figure 8. Plots of the optimization process:
a) fitness variance; b) step response for different values (with and without PID);
c) solution (population, offspring); d) fitness value

Conclusion

Tuning parameters of PID controllers is of high importance in engineering. Implementing evolutionary strategy ($\mu + \lambda$) for tuning purposes gives us great results. This method can be used to tune PID parameters for various complex systems. In our case study the algorithm searched for the controller parameters K_P(proportional gain), K_i(integral gain) and K_d(derivative gain) so that specifications for the closed-loop step response were met. The objectives were defined by the objective function, based on those objectives the controller parameters were tuned. The optimized PID controller with ES ($\mu + \lambda$) gives us great results in terms of rise time, settling time, overshoot and steady-state error.

Nomenclature

μ	number of parents.
λ	number of offspring.
y	objective parameters.
$F(y)$	objective function (fitness function).
PID	proportional integrative derivative controller.
K_P	proportional constant.
K_d	derivative constant.
K_i	integral constant.
$ITAE$	the integral time absolute error.
ES	evolutionary strategy.

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