# In CRESED PERFORM An CEO FA HYBRID OPTImIZER FOR SImuLATIOn BASED COnTROLLER PARAETERIZATIOn

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***Research Article***

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***Abstract:***
In an integrated automated design, the controller parameterization is often accomplished by using simple empirical formulae. Therefore, the resultant system often fails to adequately verify the specified values because The optimizer determines a potential superior solution based on the simulator's results. A representation of the whole system under examination forms the simulator's central component. Consequently, it is necessary to solve an optimization problem (eq. 1) [1]. actions. This study presents a way for parameterizing the controller using simulation-based optimization techniques. This lets the user specify F (ⁱ) min(F (ⁱ)��� ∈Θ(1) certain limitations, such as the complementary sensitivity function (CSF), can affect the control loop's dynamic behavior. Additionally, other optimization criteria may be used. The execution time is a major determinant of effective offline and controller internal optimization techniques, and it may be decreased by using a hybrid optimization approach. Therefore, the study compares the performance of the global Particle-Swarm-Optimization (PSO) algorithm in its straight form and the global PSO algorithm combined with the The evaluation of the actual solution is represented by the real-valued function F(), often known as the fitness function [2]. Generally speaking, punishment values are used to impose limitations. A punishment value is applied to the assessment of the actual solution in the event that a constraint is broken. The optimizer avoids and depreciates it as a result. Equation 2 is used to compute the assessment of a solution. Main_Criterion (xn) F (xn) Nelder-Mead (NM) local optimization technique to a hybrid optimizer (HO) using examples.

□ Punishment_Constraint$_j(x_n)$

## 1. Introduction

Numerous techniques were created in the discipline of operations research to aid in decision-making. The broad range of applications has been shown. In order to boost speed using a hybrid optimizer, a quick introduction to various approaches for parameterizing mechatronic controllers is provided in this study. The fundamentals of simulation optimization and the used optimization techniques are described in section 2. The use of controller parameterization is then briefly discussed for two instances in section 3. Section 4 discusses the hybrid optimizer's architecture and operation. In section 5, the hybrid optimizer's performance is assessed. The comparison and conclusions presented in the section conclude the study.

## 2. Simulationbasedcontrollerparameteri- zation

of optimization strategies [3]. Finding the global extremum throughout the whole function space is the aim of global optimization. Local approaches, on the other hand, begin at a specific location inside the search space and attempt to identify a superior answer. According to [4], controller settings might be changed while taking defined restrictions into account using simulation-based optimization. Numerous optimization techniques for various application domains are available. The NM algorithm and the PSO are explained next.

### 1.2.Particle-Swarm-Optimization

Based on simulating the movement of swarms or herds, PSO is a popular heuristic approach [5]. A particle is a single member of a swarm. Each particle's path is determined by the motion of the other swarm members as well as random influences. The algorithm's speed, lack of gradient information, and straightforward structure are some of its benefits. The vector describes each particle's location in the -th step. In the ()-th step, each particle's position is updated based on equations 3 and

jective function by the coupling of a simulator with an ptimizer[1].Itresultsinacyclicsequencebetweenthe optimizer and the simulator.

(3) assesittothesimulatorforevaluation.Accordingto the $c r^k (x^{best,k} \square x^k)$(4)

Where$c$,$c$andwarepositiveconstants,$r^k$,$r^k$,and

ToreducetheovershootofthesystemtheCSFT(s)

12 1,$i$2,$i$

aretworandomvaluesintherange[0,1].Theterm$x^{best,k}$ r$_i$epresentsthebestpreviouspositionofparticle$i$tillstep $k$and$x_{swar}^{best,k}$

asthebestknownpositionamongall parti- clesinthepopulation.Therefore, $x_{i}^{best,k}$ iscalled"simple could be used [10].The mathematical structure is:

$$T(s) \square \frac{G_R(s)*G_S(s)}{1 \square G_R(s)*G_S(s)} \quad (7)$$

nostalgia"becausetheindividualtendstoreturntothe placethatmostsatisfieditinthepast.Theterm $x_{swar}^{best,k}$ realizes the publicized knowledge, which also every in- dividual tends to [6].

**2.2.Nelder-Mead**

The simplex approach, often known as the NM algorithm, wasIt makes it possible to assess the impact of modifications to the command signal. The dynamic of the control loop may be changed by defining the CSF. Consequently, by setting 1.1 The simplex, a geometric structure first introduced in [7], employs points in the search space with n +1 the dimension; for example, for n = 2, the simplex is a triangle. The simplex is first built around a dedicated starting point. The simplex's edges, known as vertices, must be spaced equally apart from one another. The modification of the simplex in the direction of the extremum is the fundamental idea behind the method. This is often accomplished by utilizing the four methods reflect(), expand(), contract(), and shrink() to swap out the poorest vertex with a better one. [8] provides a thorough explanation of the method.

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8].

## 3. OptimizationProblem

### 3.1. ControlLoopDynamic

A transfer function GS (eq. 5) is used to characterize the system behavior under the assumption of the specified closed loop system topology [9].

$1 \square bs \square bs^2 \square \ldots \square bs^m$The amount of amplification that is allowed is restricted. The new results are KR= 12.327, KI = 17.936 and KD = 2.07. As expected the overshoot is reduced (Figure 2) while the rise time increases

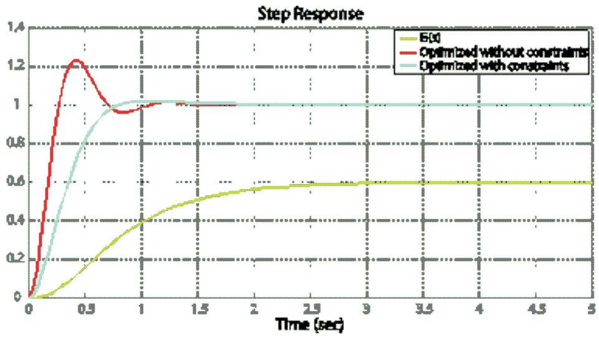


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*Fig.2.Comparisonofparameter settings*

$$G_S(s) \square K^* \frac{1 \square b_1 s \square b_2 s^2 \square \ldots \square b_m s^m}{1 \square a_1 s \square a_2 s^2 \square \ldots \square a_n s^n} \quad (5)$$

It is supposed to use a PID controller $G_R$ in the addi- tive structure (eq. 6).

$K$

### 3.2. Energy Consumption

Asanalternativetotheoptimizationbasedonthe CSF (section 3.1), the approach can also be used to minimize othercriteria,suchastheenergyconsumptionofaservo drive.Toillustratethis,aPIvelocitycontrolleraccording

$G_R(s) \square K_R \square \frac{K_I}{s} \square K_D s$ (6)toequation 9 isused.

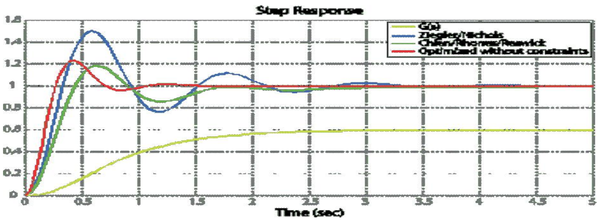
$G(s) \square K \square 1$

$1 \square$

$PI \quad P□ □ □$

$□ T□ s □ □$

(9)




The closed current loop and the whole moment of inertia are included in the controlled system model. The param- eter identification was carried out in [11] and leads to the following first order integral plus dead time system (FOIPD) (eq. 10

In Figure 1 possible attainable transition functions of a$PT_3$plant($K=0.6, a_1=0.92, a_2=0.234, a_3=0.018$)with aPIDcontrollerareshown.Themainoptimizationcrite- rionisthecontrolarea.Noconstraintsweredefined.The results of the optimization process are $K_R= 12.327$, $K_I= 17.936$ and $K_D= 2.07$.

The simulator was developed in MATLAB® Simulink® to provide more freedom in determining the quantification elements (control effort, control area, and disturbance area) and the penalty (max. overshoot = 15%). The control effort was selected as the primary criteria with an emphasis on energy consumption. Table 1 shows the results of the automated controller tuning system, which is part of the servo drive system, as well as the consequent controller parameterization.

*Table1.Controllerparameters*

| **Method** | **$K_P$[Nms/rad]** | **$T_N$[ms]** |
|---|---|---|
| AutomaticTuning (SIEMENS) | 1.309 | 8.73 |
| Optimizer | 0.9 | 5.2 |

*Fig.3.Controleffortstep response*

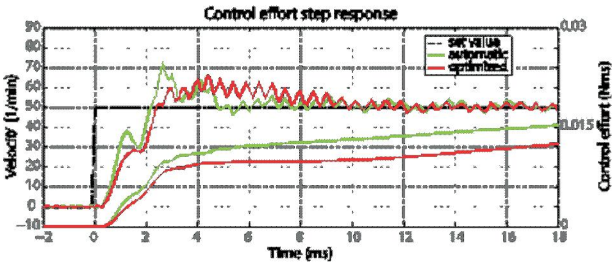



Figure3showstheresultingstepresponsesandthein- tegratedcontroleffort.Noticethattheovershootreaches the predefined limit without exceeding it. Furthermore thereductionoftheenergyconsumptionisvisibleinthe time plot, while the settling times of both variants are comparable.

## 4. Hybridoptimizer

With the aim of improving performance over a stand-alone optimization strategy, the HO in this research combines the global PSO with the local NM algorithm. The following is how the algorithm works: A limited number of calculations are made before the PSO is finished. As a result, the PSO is limited to worldwide search space investigation. Three examples from the NM algorithm are then investigated by the PSO, which realizes a local search, starting with the best, third best, and fifth best points. The best outcome of the three NM examples is the optimization solution (Figure 4). The resilience against local extremes is the rationale for beginning the local search from several sites. Research has shown that the HO's hit rate for locating the extremum is decreased when just one instance is employed [12].

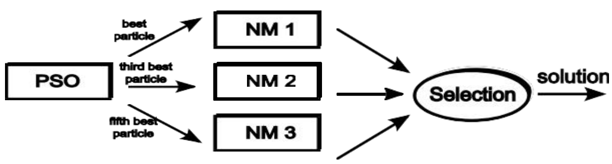


*Fig.4.Structureofhybridoptimizer*

## 5. Performance comparison

6. A self-developed modular optimization program written in C# using VisualStudio 2010 that supports several optimization techniques was used to conduct the performance testing. MATLAB® was used to implement the simulation models.Theamount of computations needed to determine the global extremum with a certain tolerance to the best known solution was compared using four distinct transfer functions (table 2). The optimization was carried out thirty times for each transfer function. Compared to the solo PSO, the HO only needs 6% to 69% of the simulator's invocations, as seen by the findings in Table 1. An optimization run's execution time is greatly decreased as a result. Additionally, the global extremum may always be detected by the HO. The intricate form of the search space explains why there are so many computations required for system three. The global extremum is located in a relatively tiny area because of the very steep slopes around it.

*Table2.Overviewofchosentestfunctions*

| Controlled System | Transfer function | Calculations | |
|---|---|---|---|
| | | PSO | Hybrid |
| 1 ($PT_3$) | $K=1, a_1=2, a_2=2, a_3=1$ | 1737 | 342 |
| 2 ($PT_3$) | $K=1, a_1 = 3.1, a_2=2.3, a_3=0.2$ | 2007 | 459 |
| 3 ($PT_3$) | $K=1, a_1=2, a_2=2, a_3=3$ | 23459 | 1464 |
| 4 ($PT_2$) | $K=1, a_1=3, a_2= 2$ | 542 | 374 |

## 7. Conclusion

When compared to the PSO algorithm alone, the hybrid optimizer's performance was significantly improved by combining the PSO and NM. The HO has the benefit of switching from the PSO's successful global optimization approach to the NM, which works better for local exploration. The amount of calculations needed is still lower even with the three NM instances. Enabling online and real-time applications requires this. However, additional research into modifying the algorithms' tuning parameter in relation to the controller parameterization issue has to be done. Additionally, it is necessary to research various optimization methods, such as the Newton's method, evolutionary algorithms, and other hybrid optimizer combinations. Additionally, it is possible to tune more complicated systems, such as a controller cascade with filters, using the simulation-based optimization process.

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