

# PERFORMANCE COMPARISON OF EVOLUTIONARY TECHNIQUES ENHANCED BY LOZI CHAOTIC MAP IN THE TASK OF REACTOR GEOMETRY OPTIMIZATION

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## KEYWORDS

PSO, Optimization, Evolutionary Algorithms, Swarm intelligence, Chaos

## ABSTRACT

In this study the performance of two popular evolutionary computational techniques (particle swarm optimization and differential evolution) is compared in the task of batch reactor geometry optimization. Both algorithms are enhanced with chaotic pseudo-random number generator (CPRNG) based on Lozi chaotic map. It is depicted the course of the reactor processes dynamical parameters for the best obtained solutions for both algorithms and numerical values of cost functions are compared. The promising results are discussed.

## INTRODUCTION

In recent years the demand for effective optimization tools for complex optimization tasks have significantly increased. For this reason a significant effort is put into development and enhancement of such methods. A group of very effective methods that had already established themselves are the evolutionary computational techniques (ECTs). Two of the most significant and potent (meta)heuristic algorithms from the ECTs field are the Differential evolution (DE) (Storn, Price, 1997) and Particle swarm optimization (PSO) (Kennedy, Eberhart 1995, Eberhart, Kennedy 2001). In the recent research (Pluhacek et al. 2013, Senkerik et al. 2013), it has been observed that through utilization of chaos based pseudo-random number generators within these heuristics their performance can be significantly improved. Thus the chaos enhanced ECTs can be effectively used to solve complex practical tasks (Pluhacek et al. 2012). In this paper the performance of both aforementioned algorithms is investigated in the task of batch reactor geometry optimization. This task represents the complex optimization problems with very slow inner dynamic. Both algorithms are enhanced with Lozi chaotic map (Spratt 2003). The newly acquired results of chaos driven PSO are compared to previously published

results of chaos enhanced DE algorithm (Senkerik et al. 2013).

The rest of the paper is structured as follows: In the next section the PSO algorithm is described in details followed by a brief description of the Lozi chaotic map that was used as the pseudo-random number generator (CPRNG) for both algorithms. In the next three sections the batch process, the batch reactor and the experiment setup are explained. The graphical and numerical results presentation and comparison follow afterwards. Finally the obtained results are briefly discussed in the last section that is followed by the conclusion.

## PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization algorithm (PSO) is the evolutionary optimization algorithm based on the natural behavior of bird and fish swarms and was firstly introduced by R. Eberhart and J. Kennedy in 1995 (Kennedy, Eberhart 1995, Eberhart, Kennedy 2001). As an alternative to genetic algorithms (Goldberg, David, 1989) and differential evolution (Storn, Price, 1997), PSO proved itself to be able to find better solutions for many optimization problems.

In the PSO algorithm the particles move through the multidimensional space of possible solutions. The new position of the particle in the next iteration is then obtained as a sum of actual position and velocity. The velocity calculation follows two natural tendencies of the particle: To move to the best solution found so far by the particular particle (known in the literature as personal best:  $pBest$  or local best:  $lBest$ ). And to move to the overall best solution found in the swarm or defined sub-swarm (known as global best:  $gBest$ ).

In the original PSO the new position of particle is altered by the velocity given by (1):

$$v_{ij}^{t+1} = w \cdot v_{ij}^t + c_1 \cdot Rand \cdot (pBest_{ij} - x_{ij}^t) + c_2 \cdot Rand \cdot (gBest_j - x_{ij}^t) \quad (1)$$

Where:

$v_i^{t+1}$  - New velocity of the  $i$ th particle in iteration  $t+1$ .

$w$  – Inertia weight value.

$v_i^t$  - Current velocity of the  $i$ th particle in iteration  $t$ .

$c_1, c_2$  - Priority factors (set to the typical value = 2).

$pBest_i$  – Local (personal) best solution found by the  $i$ th particle.

$gBest$  - Best solution found in a population.

$x_{ij}^t$  - Current position of the  $i$ th particle (component  $j$  of the dimension  $D$ ) in iteration  $t$ .

$Rand$  – Pseudo random number, interval (0, 1). The chaotic pseudo-random number generator is applied here.

The maximum velocity of particles in the PSO is typically limited to 0.2 times the range of the optimization problem and this pattern was followed in this study. The new position of a particle is then given by (2), where  $x_i^{t+1}$  is the new particle position:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (2)$$

Finally the linear decreasing inertia weight (Nickabadi et al., 2011). is used in the PSO here. Its purpose is to slow the particles over time thus to improve the local search capability in the later phase of the optimization. The inertia weight has two control parameters  $w_{start}$  and  $w_{end}$ . A new  $w$  for each iteration is given by (3), where  $t$  stands for current iteration number and  $n$  stands for the total number of iterations.

$$w = w_{start} - \frac{((w_{start} - w_{end}) \cdot t)}{n} \quad (3)$$

## CHAOTIC LOZI MAP

The Lozi map is a simple discrete two-dimensional chaotic map. The Lozi map is depicted in Fig. 1. The map equations are given in Eq. 4. Typical parameters given in literature (Sprott 2003) are  $a = 1.7$  and  $b = 0.5$ .

$$\begin{aligned} X_{n+1} &= 1 - a|X_n| + bY_n \\ Y_{n+1} &= X_n \end{aligned} \quad (4)$$

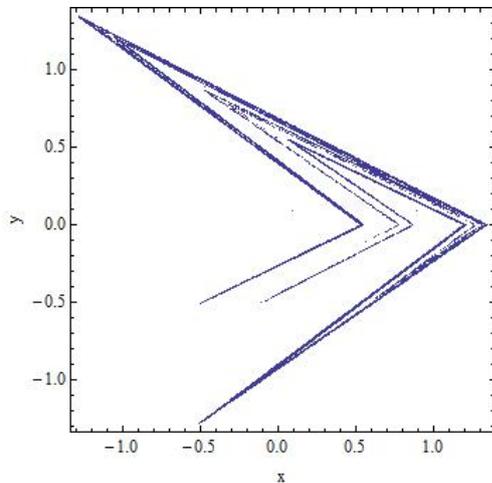


Figure 1:  $x, y$  plot of the Lozi map

## BATCH PROCESSES

The optimization of batch processes has attracted attention in recent years (Silva and Biscaia 2003, Arpornwichanop et al 2005.). Batch and semi-batch processes are of considerable importance in the fine chemicals industry. A wide variety of special chemicals, pharmaceutical products, and certain types of polymers are manufactured in batch operations. In batch operations, all the reactants are charged in a tank initially and processed according to a pre-determined course of action during which no material is added or removed. From a process systems point of view, the key feature that differentiates continuous processes from batch and semi-batch processes is that continuous processes have a steady state, whereas batch and semi-batch processes do not (Srinivasan et al. 2002a, 2002b). Many modern control methods for chemical reactors were developed embracing the approaches such as iterative learning model predictive control (Wang et al. 2008), iterative learning dual-mode control (Cho et al. 2009) or adaptive exact linearization by means of sigma-point kalman filter (Beyer et al. 2008). Also the fuzzy approach is relatively often used (Sarma 2001). Finally the methods of artificial intelligence are very frequently discussed and used. Many papers present successful utilization of either neural networks (Sjöberg and Mukul 2002, Mukherjee and Zhang 2008, Mujtaba et al. 2006 or genetic (evolutionary) algorithms (Causa et al. 2008, Altinten et al. 2008, Faber et al. 2005).

This paper presents the static optimization of the batch reactor geometry by means of chaos driven PSO algorithm with CPRNG based on Lozi chaotic map and further compares the results with previously published results of similar optimization by means of chaos enhanced Differential evolution (Senkerik et al. 2013).

## DESCRIPTION OF THE REACTOR

This research uses the mathematical model of the reactor shown in Fig. 2. The reactor has two physical inputs: one for chemical substances Chemical FK (Filter Cake) with parameters temperature- $T_{FK}$ , mass flow rate- $\dot{m}_{FK}$  and specific heat- $c_{FK}$ ; and one for cooling medium of temperature  $T_{VP}$ , mass flow rate- $\dot{m}_r$  and specific heat- $c_V$ . The reactor has one output: cooling medium flows through the jacket inner space of the reactor, with volume related to mass -  $m_{VR}$ , and flows out through the second output, with parameters mass flow rate  $m_V$ , temperature- $T_V$  and specific heat- $c_V$ .

At the beginning of the process there is an initial batch inside the reactor with parameter mass- $m_P$ . The chemical FK is then added to this initial batch, so the reaction mixture inside the reactor has total mass- $m$ , temperature- $T$  and specific heat- $c_R$ , and also contains partially unreacted portions of chemical FK described by parameter concentration  $a_{FK}$ . In general, the reaction is highly exothermic, thus the most important parameter is the temperature of the reaction mixture. This temperature must not exceed  $100^\circ\text{C}$  because of safety aspects and quality of the product. The original design

of the reactor was based on standard chemical-technological methods and gives a proposal of reactor physical dimensions and parameters of chemical substances. These values are called within this paper original parameters. For the detailed description, please refer to (Senkerik and Zelinka 2005).

The main objective of the optimization is to achieve the processing of large amount of chemical FK in a very short time.

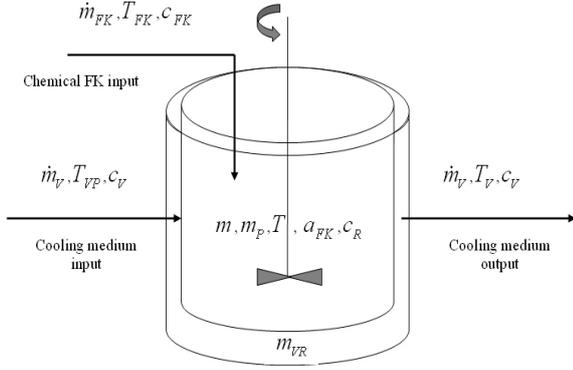


Figure 2: Batch reactor

Description of the reactor applies a system of four balance equations (5) and one equation (6) representing the term “ $k$ ”.

$$\begin{aligned} \dot{m}_{FK} &= m'[t] \\ \dot{m}_{FK} &= m[t] a'_{FK}[t] + k m[t] a_{FK}[t] \\ \dot{m}_{FK} c_{FK} T_{FK} + \Delta H_r k m[t] a_{FK}[t] &= \\ &= K S (T[t] - T_V[t]) + m[t] c_R T'[t] \\ \dot{m}_V c_V T_{VP} + K S (T[t] - T_V[t]) &= \dot{m}_V c_V T_V[t] + m_{VR} c_V T'_V[t] \end{aligned} \quad (5)$$

$$k = A e^{-\frac{E}{RT[t]}} \quad (6)$$

## EXPERIMENT SETUP

The control parameters of PSO algorithm were set following way:

Population size: 50  
Iterations: 200  
 $w_{start}$ : 0.9  
 $w_{end}$ : 0.4  
 $v_{max}$ : 0.2

The control parameters of DE algorithm were set as follows:

Population size: 50  
Generations: 200  
 $F$ : 0.8  
 $CR$ : 0.8

## RESULTS COMPARISON

In this section the results of chaotic PSO algorithm are presented and compared with the results of chaotic Differential evolution (ChaosDE). Both algorithms used CPRNG based on Lozi Chaotic map. Table 1 contains the overview of optimized and original parameters where the internal radius of reactor is expressed by parameter  $r$  and is related to cooling area  $S$ . Parameter  $d$  represents the distance between the outer and inner jackets and parameter  $h$  means the height of the reactor. The original design of the reactor was based on standard chemical-technological methods and gives a proposal of reactor physical dimensions and parameters of chemical substances. These values are called within this paper *original parameters (values)*. The courses of the reactor processes dynamical parameters for the best obtained solutions for both PSO and DE are compared in figures 3 – 8. Table 2 contains the simple statistical evaluation of the repeated runs of both algorithms.

Table 1: Optimized reactor parameters, difference between original and the optimized reactor

Parameter	Range	Original value	Optimized value (PSO)	Optimized value (DE)
$\dot{m}_{FK}$ [kg.s <sup>-1</sup> ]	0 – 10.0	0 - 3	0.06732	0,06935
$T_{VP}$ [K]	273.15 – 323.15	293.15	273.664	276.819
$\dot{m}_V$ [kg]	0 – 10.0	1	3.7451	4,9832
$r$ [m]	0.5 – 2.5	0.78	1.3896	1.0008
$h$ [m]	0.5 – 2.5	1.11	1.0668	1.0088
$d$ [m]	0.01 – 0.2	0.03	0.091965	0.0216

Table 2: Statistical overview and comparison

Algorithm	Avg CF	Median CF	Max CF	Min CF	StdDev
Chaos PSO with Lozi Map	26792.1	28557.4	31615.9	21560.3	3991.73
Chaos DE with Lozi Map	<b>21117.64</b>	<b>21113.13</b>	<b>21232.46</b>	<b>21046.02</b>	40.4

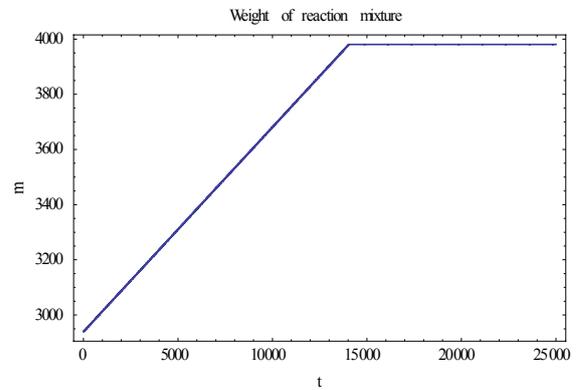


Figure 3: Weight of reaction mixture (PSO)

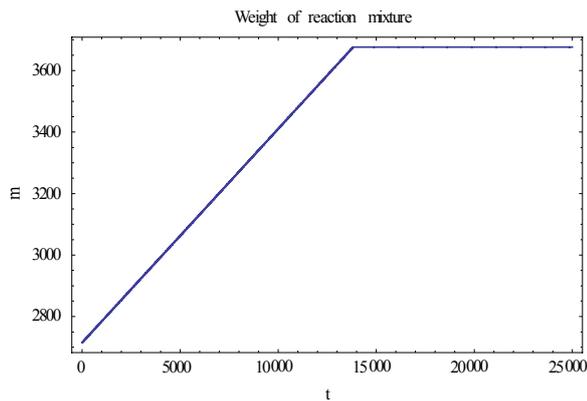


Figure 4: Weight of reaction mixture (DE)

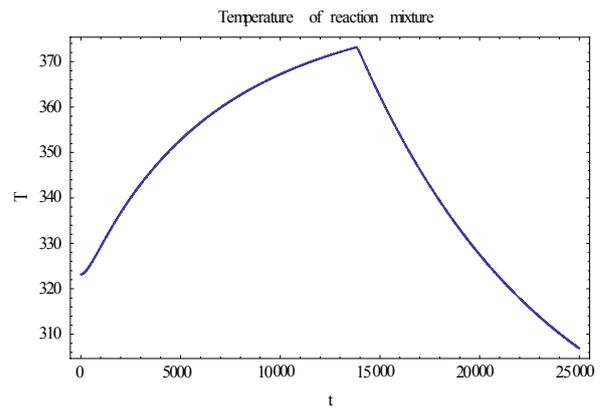


Figure 8: Temperature of reaction mixture (DE)

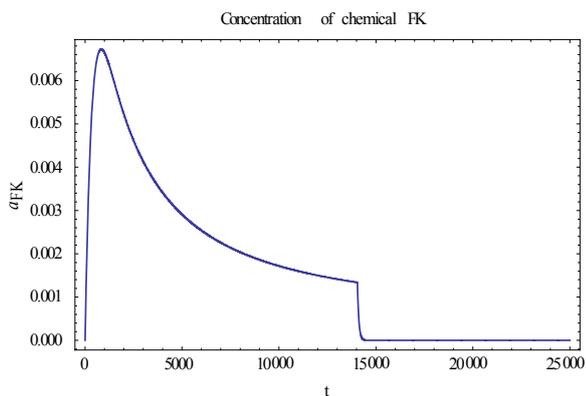


Figure 5: Concentration of chemical FK (PSO)

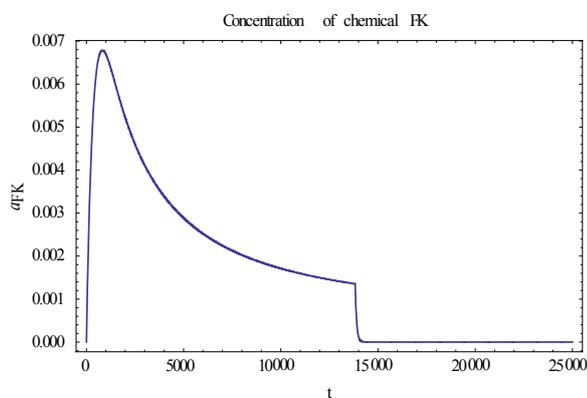


Figure 6: Concentration of chemical FK (DE)

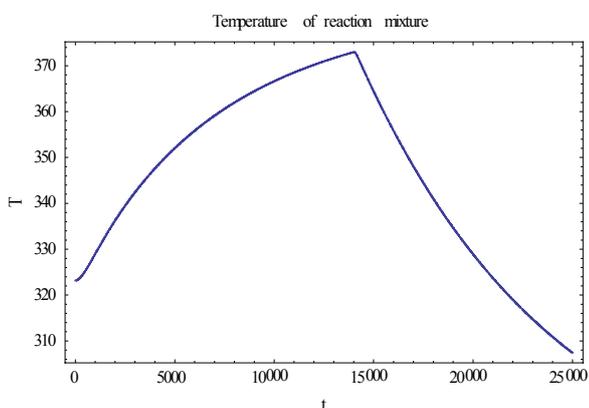


Figure 7: Temperature of reaction mixture (PSO)

## BRIEF ANALYSIS OF THE RESULTS

Compared results in Table 2 indicate that the DE algorithm enhanced with Lozi chaotic maps seems to perform better on the task of reactor geometry optimization than chaotic PSO algorithm. However the evaluation of best found solutions (Table 1) depicted in figures 3 – 8 seems to indicate that the difference in final batch process behavior is not very perceptible. Both algorithms managed to find successful solution as none of the critical values were exceeded. The concentrations of chemical substances and weights of reaction mixture are comparable, as well as the courses of temperature.

## CONCLUSION

In this paper the performance of PSO algorithm driven by Lozi chaotic map was compared to the performance of Differential evolution with similar chaos based PRNG in the task of batch reactor optimization. The final solution was evaluated and compared. Despite the differences in final cost function value in favor of the DE algorithm, it can be stated that both algorithms managed to obtain successful reactor designs. The chaos driven evolutionary computational techniques seem to be very promising tools for optimization of very complex and slow dynamic processes such as the task presented in this work and future research shall investigate this further.

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