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Evaluation of Cuckoo Search Usage for Model Parameters Estimation

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ABSTRACT

Cuckoo Search is gaining a lot of attention as a new soft computing technique inspired by nature,in this research the application of Cuckoo Search for solving the problem of estimating the parameters of a nonlinear model is investigated from both aspects of efficiency and robustness. Using a case study of estimation of parameters of a nonlinear model for the cutting tool temperature in an industrial metal cutting system, Cuckoo search was proved to be efficient in comparison to other approaches like genetic algorithms and particle swarm optimization. The paper also investigates the sensitivity of the Cuckoo Search performance to the variation of its tuning parameters, results showed the high efficiency and robustness of Cuckoo Search when applied to the problem of parameter estimation of a nonlinear model.

Keywords:

Cuckoo Search , Parameter estimation, Nonlinear systems

1. INTRODUCTION

Nature inspired algorithms use inexact approaches to solve computationally hard problems, they include different approaches like genetic algorithms(GAs), neural networks(NN) , particle swarm optimization(PSO)[1], Bat Algorithm [2], Water drops algorithm [3], fuzzy logic [4] and Cuckoo Search(CS).
As theses algorithms proved to be efficient, a lot of researches investigated their usage to solve various complex industrial and engineering problems, among these problems is the system modeling problem. System modeling is the concept of representing the behavior of a system by a mathematical equation or a set of mathematical equations. Parameter estimation of a model is a complex optimization problem that standard analytic approaches might fail to solve [5].
To estimate these parameters, search procedures like least square estimation, likelihood and instrumental variable methods [6] can be applied, these procedures aim to minimize the error between the actual model and the predicted model, although they can usually provide good results, they have no exact solution and they suffer from efficiently reduction in the presence of noise.
As traditional techniques would fail to reach satisfactory solutions for the parameter estimation problem, different nature inspired algorithms have been investigated in this area; Multi-objective Genetic Algorithm (MOGA) was applied to estimate the parameters of pressure swing adsorption model [7], PSO was used to build a model to predict the thickness and surface roughness of printed patterns in roll-to-roll printing systems which is a nonlinear system with complicated dynamics [8]. Fuzzy classification was used to build a model for the nebulization quality of oil flames [9] which is an important characteristic exhibited by combustion processes of petroleum refinery furnaces
This paper investigates the use of Cuckoo search as a nature inspired algorithm for solving the problem of parameter estimation of a nonlinear model, a real case study for modeling the cutting tool temperature in an industrial metal cutting system is also presented. After the current introductory section the paper is organized as follows, a section is presented to elaborate the system modeling problem followed by a section on cuckoo search. After that another section shows a case study of the application of a cuckoo search to estimate the parameters of a nonlinear model for the cutting tool temperature.

2. SYSTEM MODELING

System modeling has two main stages, the first stage is to estimate the structure of the model according to the system dynamics and the second stage is to estimate the unknown parameters of the model.

2.1 System Modeling Procedure

A conventional system modeling process can be applied using the following steps:-

Step 1: Collect real input and output data from the process to be identified, usually 70% of the available data-set is considered as training data, the rest is the validation data.
Step 2: Define a number of candidate model structures.
Step 3: Select a model structure hypothesis h_θ.
Step 4: Estimate the model parameters using the training data.
Step 5: Validate the model using the set of validation data.

The flowing sections elaborate some of the main concepts within these steps.

2.2 Model Structure Hypothesis

For model with numeric output, the following approaches can be used to select a model structure hypothesis:

(1) Linear Regression

(2) Polynomial Regression

(3) Nonlinear Regression

2.2.1 System Modeling using Linear Regression:. Linear regression is used if the system to be modeled is considered linear. A linear hypothesis is developed to predict the output of a linear system for a given input. The hypothesis equation for linear regression is declared as follows:

$$h_\theta(x) = \theta_0 + \sum_{i=1}^{n} x_i\theta_i \tag{1}$$

where:
$h_\theta(x)$: predicted output value for the x input vector.
n:number of system inputs.
x:input vector $[x_0\ x_1\ x_2\ x_3\ ....x_n]$,$x_0 = 1$
θ :the parameters that need to be determined, $[\theta_0\ \theta_1\ \theta_2\ ....\theta_n]$.

2.2.2 System Modeling using Polynomial Regression:. Polynomial regression models a system using polynomial equation. A polynomial equation is formed from variables and constants and using only the operations of addition, subtraction, multiplication to form a polynomial model.
A polynomial model can be rewritten as a linear model by defining terms like x^2, x^3 as distinct independent variables in a multiple linear regression model. For example the hypothesis of a polynomial model with a single input x_1 can be written as follows:-

$$h_\theta(x) = \theta_0 x_0 + \theta_1 x_1 + \theta_2 (x_1)^2 + \theta_3 (x_1)^3 \tag{2}$$

Defining new inputs as the square and cube of x_1 will enable as to solve the modeling problem exactly as if it is a linear regression problem.

2.2.3 System Modeling using Nonlinear Regression:. Most complex systems are by nature nonlinear, a nonlinear model will have at least one of its parameters appears nonlinear, linear regression or polynomial regression will fail to represent the system.
A nonlinear model can take various nonlinear structures, however the problem of parameter estimation of a nonlinear model becomes very complex. In the case study included in this research, modeling of the cutting tool temperature is done using a nonlinear model

2.3 Cost Function

A cost function $J(\theta)$ represents the difference between the actual values of outputs and the predicted value calculated using $h_\theta(x)$. Different equations can be used as a cost function, among them are residual standard deviation and sum of square error(SSE). SSE is declared for n inputs (where x_0 = 1) as follows:

$$J(\theta) := \frac{1}{m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2 \tag{3}$$

where $J(\theta)$ is the cost function; x^i is the training data. i represents the training sample. y_i is actual known output. m is the number of training examples. The cost function $J(\theta)$ represents the calculated error of the model based on certain values of θ.
θ can be estimated by solving the minimization problem of $J(\theta)$. Traditional techniques like normal equation can be applied when the size of the input vector is not large otherwise iterative techniques like gradient decent would be more efficient.
The cost function of linear regression is always a convex function, gradient decent will always reach an optimum solution without being affected by the choice of initial solution. Regularization modification can be applied to the cost function to prevent over fitting, where the proposed hypothesis fit the training set very well but fail to generalize to new examples.
When solving the regression problem of nonlinear systems, the minimization of the cost function will produce normal equation with nonlinear parameters that does not have an exact solution, although iterative procedures like Taylor series, steepest descent and Levenberg-Marquardt methods could be applied to solve the problem, these procedures are not optimal, they suffer from slow convergence and the sensitivity to the initial solution.
To get a sense of the complexity of the parameter estimation of a nonlinear model problem, the following hypothetical nonlinear system is defined:

$$y(x) = 4 * cos(45 * x) - 2 * sin(10 * x) \tag{4}$$

Assuming that the structure of this hypothetical model is already known but without the values of the parameters, the hypothesis function ($h_\theta(x)$)can be declared as follows:

$$h_\theta(x) = 4 * cos(\theta_0 * x) - 2 * sin(\theta_1 * x) \tag{5}$$

The role of parameter estimation is to figure out the values of θ_0 and θ_1 ,assuming that the exploration range for these values is from 0 to 50, the search space for minimizing the cost function $J(\theta)$ -as shown in figure 1- is a non-convex search space. The quality of a solution proposed by a traditional technique for such a problem will be affected by the arbitrary staring search point and can be easily trapped in local optima.
To overcome the complex difficulties of parameter estimation of nonlinear models, Nature-Inspired learning algorithms had been applied to solve the nonlinear regression problem [10]. In this research, Cuckoo Search as one of these algorithms is applied to solve this complex problem.

3. CUCKOO SEARCH

3.1 Introduction to Cuckoo Search

Cuckoo Search is a search algorithm inspired the breeding behavior of cuckoos, cuckoo breeding can be described as an act of parasitism, a cuckoo bird lay its egg in other birds nests and relay on that bird for hosting the egg, sometimes the other bird discover that an egg is not their own, it might demolish the alien egg or just move to another nest.
To protect its egg from being discovered, a cuckoo might imitate the shape, size and color of the host eggs, some cuckoos might take an aggressive action and remove other native eggs from the host nest to increase the hatching probability of their own eggs, a hatched cuckoo chick will also throw other eggs away from nest to improve its feeding share [11].
Cuckoo Search captures the concepts of cuckoo breeding by formulating candidate solutions for an optimization problem as Cuckoo eggs in different nests, the search starts with a fixed number of nests each contain a candidate solution to form an initial generation of solution, this generation evolve from one iteration to another while a fraction of the solutions in nests will be eliminated and replaced by new solution to model the concept of alien egg discovery in a real cuckoo world.

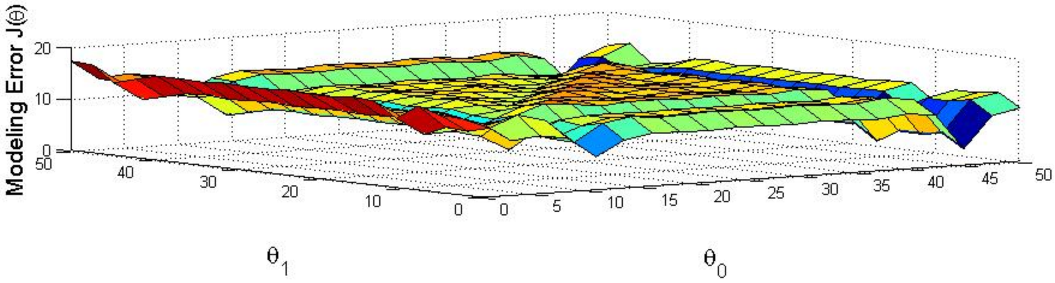

Fig. 1. Error surface for the system given in Equation 5

CS depends on Lèvy flight as the random walk used to generate new solution(cuckoos) from current solution according to the following equation:-

$$cuckoo_i^{(t+1)} = cuckoo_i^{(t)} + \alpha \oplus L\acute{e}vy(\lambda), \tag{6}$$

where $cuckoo_i^{(t+1)}$ is the value of the i^{th} Cuckoo at instance t, α:step size, usually chosen to be equal to one, λ: Lèvy distribution coefficient $(1 < \lambda < 3)$

Some of new solutions are produced from best current solutions by Lvy walks, this give CS the capabilities of local search with the ability of self-improvement as in memetic algorithms. Also some of the new solutions are produced away from the best current solutions, this decreases the opportunity to be trapped in local minima, and enrich the versification of search as in Tabu search. The implementation of CS also ensures elitism as the best nest will be kept from iteration to another.

The main advantage of Cuckoo search is its simplicity of application as CS has fewer parameters that need to be tuned before starting the search compared with other techniques, in contrast, PSO needs tuning of mainly three parameters: Inertia weight, effect of self-confidence and effect of social impact, the range of tuning parameters of PSO affect the quality of search dramatically [12]. GA needs to tune the crossover rate and mutation rate and to choose between various selection methodologies.

3.2 Cuckoo Search Scheme

The following procedures list the outlines for application of Cuckoo Search **Procedure Cuckoo Search ()**

-Begin
-Call Initial Setup()
-Call Initial population()
-Call Update Population()
-Display output results
End

Procedure Initial Setup()
-Begin
-Set the number of dimensions :dim
-Set upper and lower bounds :ub ,lb
-Set the number of nests :n
-Set Maximum Iteration:maxIter
-Define your hypothesis function: $h_\theta(x)$
-Define the cost function:$J(\theta)$
-Set the parameters of Levy flights:β
-Set Discovery rate of alien eggs/solutions :pa
End

Procedure Create Initial population()
Begin
-Create random n nests (initial population) of dimension dim without violating ub ,lb
-Set initial minimum cost to a very high value
-Evaluate cost of initial population using $J(\theta)$
-Set minimum cost to the cuckoo with minimum cost
End

Procedure Update Population()
Begin
-Loop from 1: maxIter
-create proposed nests using current nests values and Levy flights with β with following constraints
  best nest is not altered
  all solutions within bounds
-Evaluate cost of the proposed nests using $J(\theta)$
-Perform elitism
-Create new nests by mutating current nests randomly based on pa
-evaluate fitness of the proposed nests using $J(\theta)$
-preform elitism
End Loop
End

4. APPLICATION OF CUCKOO SEARCH TO NONLINEAR MODEL PARAMETERS ESTIMATION

4.1 Case study:Nonlinear Model of Cutting Tool Temperature

Machining is cutting a piece of raw material into a desired form and size by a controlled process of material removal, the cutting forces of this process is converted into heat and the cutting tool suffers from very high temperature. The high temperature of the cutting tool decreases the tool life and affects the surface finish and geometrical dimensions of the product and thus the quality of the whole process.

Researches regarding finding the model for the cutting temperature have shown that the value of this temperature is mainly dependent on the following three variables:

(1) Depth of the cut (mm)
(2) Cutting feed rate (mm/rev)
(3) Cutting speed (m/min)

Moreover, An empirical model exits for cutting temperature [13],the model is declared as follows:

$$h_\theta(x) = \theta_0 * x_0^{\theta_1} * x_1^{\theta_2} * x_2^{\theta_3} \tag{7}$$

where x_0, x_1, x_2 are the depth of cut, cutting feed rate and cutting speed respectively.
The case study of this research will be to estimate the parameters for the nonlinear model of cutting tool temperature.The data measured experimentally for the cutting tool PO5 with the 38CrNi3Mo metal of the workpiece is used, the system is shown in figure 2.

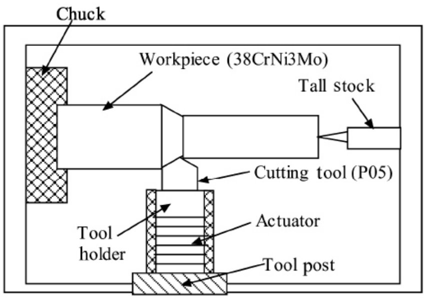

Fig. 2. Metal Cutting Machine

4.2 Cost Function

For the case study, the cost function $J(\theta)$ aims to minimize will be the residual standard deviation declared as follows:

$$J(\theta) := \sqrt{\frac{\sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2}{n-2}} \tag{8}$$

where $J(\theta)$ is the cost function, y is actual known output and m is the number of training examples. Solving this parameter estimation problem means finding values for the model parameters which will minimize the error between outputs from predicted model and actual outputs. The data set used for learning about the model is the same as declared in [13] which is acquired experimentally.

4.3 Setting up Cuckoo search Algorithm for Parameter Estimation

Table 1 presents the parameters used for the applied cuckoo search

Table 1. Tuning Parameters.

Parameter	**value**
Number of nests	10
Discovery rate of alien solutions (p_a)	0.25
Levy exponent (β)	1.5
Maximum Iteration	300
Number of dimensions	4
Lower bounds	[0, -10, -10, -10]
Upper bound	[1000, 10, 10, 10]

4.4 Results

CS succeeded in estimating the parameters of the temperature model, by the end of search the Residual standard deviation reached 5.129. Table 2 shows the outputs of the CS.
Figure 3 shows the actual temperature versus the temperature calculated using the estimated parameters by CS for the nonlinear model. Figure 4 shows the reduction of the cost from iteration to another.

Table 2. Cuckoo Search Results.

Parameter	**value**
θ_0	1410.29
θ_1	0.032
θ_2	0.082
θ_3	0.158
Residual standard deviation	5.129

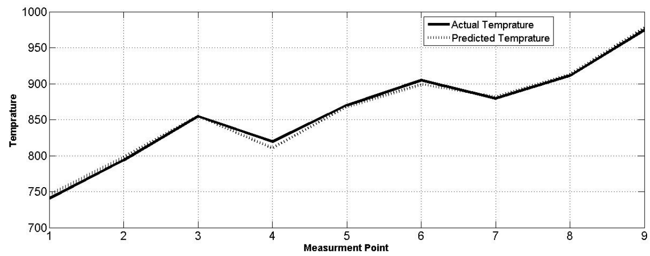

Fig. 3. Actual Temperature vs. predicted Temperature

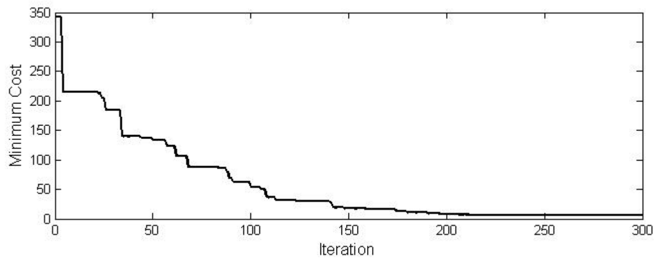

Fig. 4. Minimum cost vs. Iteration

4.5 Effect of Tuning Parameters on Efficiency of Results

One of the very important aspects of a search algorithm is how much it is vulnerable to variations in the tuning parameters, to check the robustness of cuckoo search, a number of searches are initiated with different tuning parameters and results are recorded. The effects of the variation of β , n and p_a are investigated by executing a 100 different searches for the each of the following cases:

(1) $1.1 < \beta < 2$, n=20 and $p_a = 0.1$
(2) $beta = 1.5$, n=20 and $0.1 < p_a < 0.5$
(3) $beta = 1.5$, $10 < n < 30$ and $p_a = 0.1$

For each case the values for the minimum cost, maximum cost and average cost were recorded. Table 3 shows the output of the CS search when running using different values for tuning parameters, figure 5 shows the convergence of the Cuckoo Search using different values of nests, figure 6 shows the Effect of pa on quality of CS.

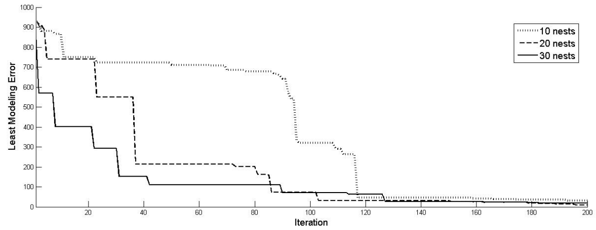

Fig. 5. Convergence of the CS evolutionary process

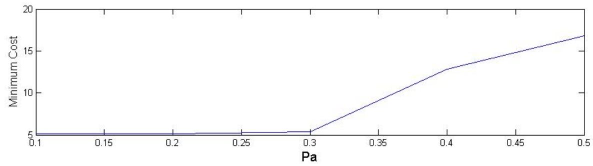

Fig. 6. Effect of pa on quality of search

4.6 Discussion

As shown from the results, CS succeeded in finding values for the parameters of the nonlinear model.
The same problem of consideration has been attempted by different researchers using different techniques [14] like least square, GAs and PSO .To prove the efficiency of using CS for nonlinear parameter estimation. Table 4 shows a comparison between residual standard deviation for the models produced by these techniques and CS.

Table 4. Comparison of Results of different procedures

Search Procedure	Residual standard deviation
Cuckoo search	5.129
Particle Swarm Optimization	5.129
Genetic algorithms	5.187
Least square	5.695

It is also clear from the results that it is easy to tune CS, the results were not affected much with the variation of tuning parameters , however p_a should be chosen less than 0.25,this is demonstrated by figure 6 which shows a decline in the quality of the solution for $p_a > 0.3$.

5. CONCLUSION

Cuckoo Search is a powerful search algorithm that it inspired by the breeding behavior of cuckoos. It has been used successfully in many areas. In this research, the usage of Cuckoo Search in solving the parameter estimation problem for nonlinear systems is investigated. This problem typically presents difficulties to traditional parameter estimation techniques which basically depend on linearizing the system in order to apply available algorithms for linear systems, also as most of these traditional techniques are based on gradient descent technique, the search might be trapped at a local optimal solution.
Cuckoo Search succeeded in estimating the values of the parameters for the nonlinear model for the cutting tool temperature in a cutting machine. CS reached a better solution than genetic algorithms and least square and although the result acquired by Particle Swarm Optimization is the same as CS. CS has a very better advantage that it does not need exhaustive tuning like Particle Swarm Optimization. Moreover, the research also investigated the effect of variation of the tuning parameters of Cuckoo Search on the quality of search,it has been shown that within a wide range, CS can be an efficient search algorithm. It is anticipated that Cuckoo Search will play a very important role in solving complex optimization problems.

6. REFERENCES

[1] Nasko Atanasov and Alexandar Ichtev. Closed-loop system identification with recursive modifications of the instrumental variable method. *Informatica*, 22(2):165–176, April 2011.

[2] A. T. Fleury, F. C. Trigo, and F. P. R. Martins. A new approach based on computer vision and non-linear kalman filtering to monitor the nebulization quality of oil flames. *Expert Syst. Appl.*, 40(12):4760–4769, September 2013.

[3] I. Kamkar, M.-R. Akbarzadeh-T, and M. Yaghoobi. Intelligent water drops a new optimization algorithm for solving the vehicle routing problem. In *Systems Man and Cybernetics (SMC), 2010 IEEE International Conference on*, pages 4142–4146, 2010.

[4] Sameh Kessentini, Dominique Barchiesi, Thomas Grosges, Laurence Giraud-Moreau, and Marc Lamy de la Chapelle. Adaptive non-uniform particle swarm application to plasmonic design. *Int. J. Appl. Metaheuristic Comput.*, 2(1):18–28, January 2011.

[5] Yang Liu and Fan Sun. Parameter estimation of a pressure swing adsorption model for air separation using multi-objective optimisation and support vector regression model. *Expert Syst. Appl.*, 40(11):4496–4502, September 2013.

[6] Ginés Moreno and Vicente Pascual. Programming with fuzzy logic and mathematical functions. In *Proceedings of the 6th international conference on Fuzzy Logic and Applications*, WILF'05, pages 89–98, Berlin, Heidelberg, 2006. Springer-Verlag.

[7] Triet Nguyen-Van and N. Hori. New class of discrete-time models for non-linear systems through discretisation of integration gains. *Control Theory Applications, IET*, 7(1):80–89, 2013.

[8] M. Papoutsidakis, G. Gkafas, S. Kanavetas, and G. Chamilothoris. Modeling and simulated control of non-linear switching actuation systems. In *Proceedings of the 8th WSEAS international conference on System science and simulation in engineering*, ICOSSSE '09, pages 97–102,

Table 3. Effect of CS Tuning Parameters on quality of search

β	n	p_a	Minimum Cost	Maximum Cost	Average Cost
$1.1 < \beta < 2$	20	0.1	5.129	5.129	5.129
1.5	20	$0.1 < p_a < 0.5$	5.129	16.801	9.061
1.5	$10 < n < 30$	0.1	5.129	5.199	5.133

Stevens Point, Wisconsin, USA, 2009. World Scientific and Engineering Academy and Society (WSEAS).

[9] Dongyong Yang, Jinyin Chen, and N. Matsumoto. Particle swarm optimization with adaptive parameters. In *Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing, 2007. SNPD 2007. Eighth ACIS International Conference on*, volume 1, pages 616–621, 2007.

[10] Xin-She Yang. *Nature-Inspired Metaheuristic Algorithms*. Luniver Press, 2008.

[11] Xin-She Yang. Metaheuristic algorithms for self-organizing systems: A tutorial. In *Self-Adaptive and Self-Organizing Systems (SASO), 2012 IEEE Sixth International Conference on*, pages 249–250, 2012.

[12] Xin-She Yang and S. Deb. Cuckoo search via levy flights. In *Nature Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on*, pages 210–214, 2009.

[13] Liu Yi-jian, Zhang Jian-ming, and Wang Shu-qing. Parameter estimation of cutting tool temperature nonlinear model using pso algorithm. *Journal of Zhejiang University Science A*, 6(10):1026–1029, 2005.

[14] J.X. Zhou. Ga algorithm for cutting experiment data drawing. *Journal of Southwest Petroleum Institute*, 29(3):1062–63, 1998.

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