Swarm and Evolutionary Computation 32 (2017) 68–84

Contents lists available at ScienceDirect

Swarm and Evolutionary Computation

journal homepage: www.elsevier.com/locate/swevo

# Swarm and evolutionary computing algorithms for system identification and filter design: A comprehensive review

Akhilesh Gotmare, Sankha Subhra Bhattacharjee, Rohan Patidar, Nithin V. George*

*Department of Electrical Engineering, Indian Institute of Technology Gandhinagar, Gujarat 382355, India*

ARTICLE INFO

*Article history:*
Received 10 August 2015
Received in revised form
10 June 2016
Accepted 22 June 2016
Available online 23 June 2016

*Keywords:*
System identification
Filter design
Swarm intelligence
Evolutionary computing
Hammerstein model
Chaotic system

ABSTRACT

An exhaustive review on the use of structured stochastic search approaches towards system identification and digital filter design is presented in this paper. In particular, the paper focuses on the identification of various systems using infinite impulse response adaptive filters and Hammerstein models as well as on the estimation of chaotic systems. In addition to presenting a comprehensive review on the various swarm and evolutionary computing schemes employed for system identification as well as digital filter design, the paper is also envisioned to act as a quick reference for a few popular evolutionary computing algorithms.



**Contents**



## 1. Introduction

Identification as well as parameter estimation of linear as well as nonlinear systems have been of considerable interest to the research community over many years [15,140,168,267,167]. This interest can be attributed to the practical applications of system identification principles in diverse fields of science and technology [169]. The basic objective of system identification task is the estimation of an equivalent model which imitates the system behaviour. In a conventional system identification approach, a gradient descent algorithm is employed in updating the model parameters with an objective of minimizing the mean square error (MSE) between the system and model response. The most frequently used adaptive algorithms are the ones based on the least mean square (LMS) algorithm [80,316]. Several improvements have been reported to either enhance the convergence or to improve the accuracy of modelling [149,103,44,259,334].

The error surface in most of the system identification scenarios discussed above is multimodal and thus a conventional gradient descent approach may converge to a sub-optimal solution [48]. In an endeavour to overcome this limitation of traditional gradient descent algorithm based system identification methods, the system identification task may be formulated as an optimization problem that can be solved using a structured stochastic search strategy like swarm and evolutionary computing algorithms. Several works have been reported on the use of swarm and evolutionary computing algorithms for identifying linear and non-linear systems. In this

* Corresponding author.
*E-mail addresses:* akhilesh_gotmare@iitgn.ac.in (A. Gotmare), sankha.bhattacharjee@iitgn.ac.in (S.S. Bhattacharjee), rohanpatidar@iitgn.ac.in (R. Patidar), nithin@iitgn.ac.in (N.V. George).

http://dx.doi.org/10.1016/j.swevo.2016.06.007

paper, an attempt has been made to present a comprehensive review on the use of computational intelligence techniques like genetic algorithm (GA) [101,57,314,100], differential evolution (DE) [270,271,233,235] and particle swarm optimization (PSO) algorithms [231,139] in effective identification of systems including infinite impulse response (IIR), chaotic and Hammerstein systems.

In addition to the various offline applications of swarm and evolutionary computing algorithms based on the principles of system identification, several online case studies have been reported in other related areas of systems engineering including controller design in active noise control (ANC) systems [244] A PSO based ANC system has been presented in [242] and nonlinear [192,94] as well as multichannel versions [95] of the same has been also reported. Bacterial foraging optimization (BFO) algorithm based ANC schemes have also been designed in the recent past [97,98]. A quantum behaved PSO [76,182] based online system identification scheme has been applied for controlling quality of service offered by a web server in [77].

In order to give the readers a flavour of the various popular swarm and evolutionary computing algorithms, an attempt has been made in this work to visualize the algorithms as a single flow diagram with multiple parallel paths as shown in Fig. 1. In addition to GA, DE and PSO, the diagram also presents a cuckoo search algorithm (CSA), which is a recently proposed swarm intelligence scheme [328]. In the diagram, the agents are treated as chromosomes in the case of GA, vectors in DE, particles in PSO and nests of cuckoo birds in case of CSA. As evident from the figure, the initial processes involved in all the algorithms considered are similar and mostly involve a random initialization of agents across the search space. The major difference is in the type of inspiration from nature which led to the development of these algorithms.

The rest of the paper is organized as follows. The various swarm and evolutionary computing methodologies employed in IIR system identification as well as filter design are reviewed in Section 2. A short review on the various system identification methods which uses a Hammerstein model is made in Section 3. The use of evolutionary computing algorithms for chaotic system identification has been reviewed in Section 4 and the concluding remarks are drawn in Section 5. In Sections 2–4, considerable attention has been made in presenting a time-line of research activities in the corresponding areas and in briefly discussing the popular swarm and evolutionary computing algorithms widely used in these areas of research.

## 2. IIR system identification and filter design

It has been reported that a practical system can be modelled with lesser number of coefficients using an IIR filter in comparison with an FIR filter. Even though there are concerns on stability, this property of IIR filters have made them a popular candidate for practical system identification and filter design [48]. In a basic IIR system identification task, modelling of a practical system is attempted using an adaptive IIR filter. The error surface involved in the modelling process can be uni-modal or multi-modal depending on the order of the modelling attempted. The error surface is typically multi-modal when under or over order modelling is performed. The nature of the error surface in an IIR system identification problem has been discussed in detail in [126] and the effect of the filter structure on the error surface has been studied in [205].

The use of a traditional gradient search approach in achieving IIR system identification may result in sub-optimal solutions due to the multi-modal nature of the error surface. In addition, the methods based on hyper-stability require systems to satisfy the strict positive realness (SPR) criterion, which may not be always feasible in practical cases [283]. Formulating the IIR system identification task as an evolutionary computing algorithm based optimization task can help in overcoming these difficulties. In addition, due to the derivative free approach followed in an evolutionary computing scheme, no assumptions need to be made on the nature of the error surface [283,74]. The basic block diagram of an IIR system identification task is shown in Fig. 2, where $x(n)$ is the training signal, $y(n)$ is the system output (with additive noise), $\hat{y}(n)$ is the model output and $e(n) = y(n) - \hat{y}(n)$ is the error signal. In an evolutionary computing approach, the adaptive weights of the model are updated in such a way as to minimize the cost function given by $\xi(n) = \mathrm{E}[e^2(n)] \approx e^2(n)$.

One of the pioneering articles in the field of evolutionary computing algorithm based adaptive system identification is the work by Etter et al. [74], where the authors presented the identification of a two-pole system using GA and illustrated its ability to distinguish between local and global optima for uni-modal and bi-modal error surfaces. The performance offered by GA was compared with that of a completely random test. GA was shown to offer similar performance as that of random test for uni-modal error surface and was reported to provide enhanced modelling accuracy for a bi-modal error surface. However, the authors did not claim convergence to global optima. In addition, a quantitative measure of the performance was not presented in the work.

A set of learning automata based IIR system identification schemes has been proposed in [283]. The authors have reported a scheme based on single automaton, another based on a team of automata and a third one which employs gradient descent along with learning automaton. Global convergence was reported in the work. Another stochastic learning automata (SLA) based approach has been demonstrated in [200]. In [199], Nambiar and Mars have attempted to solve the IIR system identification task as a GA as well as a simulated annealing (SA) based optimization problem. The authors also designed a set of hybrid techniques, which take roots from GA and SA to introduce a stopping condition in the global search process. A higher order IIR system was formulated as a cascade of second order IIR filters to improve stability and the parameters of the component filters were identified using GA, SA as well as the hybrid algorithms proposed in the paper. Of the cascade, lattice and parallel IIR structures adapted using GA explored in the paper, cascade and lattice structures failed to converge and the parallel form has been shown to achieve best convergence performance. Global optimum solution was achieved using SA and the hybrid methods. However, the time taken to converge was more in the case of SA in comparison with GA. In [41], the adaptive SA (ASA) optimization algorithm has been applied to some signal processing applications including IIR filter design.

In an endeavour to improve the convergence characteristics, reduce the sensitivity to parameters, enhance the search mechanism and to simplify the implementation of a GA based IIR system identification scheme, a new mechanism based on a genetic search optimized gradient descent algorithm [221] has been reported in [208,209]. The proposed scheme incorporates mutation into a gradient descent algorithm for improving the searching ability and has been shown to provide enhanced performance in terms of convergence speed and finding global optima in comparison with simple GA, LMS algorithm as well as the gradient lattice algorithm. A short survey of the various gradient descent and GA based IIR system identification schemes has been presented in [209]. Two variants of modified GA has been applied for parameter identification of linear and nonlinear IIR filters in [329]. Genitor, a steady state GA [315] was applied for the IIR system identification problem in [175] and has been demonstrated to outperform the regular GA. Interestingly, in the work, the lattice structure has been shown to provide better results in comparison