

# The Applications of Computational Intelligence (Ci) Techniques in System Identification and Digital Filter Design

Jainarayan Yadav<sup>1</sup>, Sanjay Gurjar<sup>2</sup>

<sup>1</sup>M.Tech (Ece), Bhagwant University Ajmer & Mb No: 07542029216,

<sup>2</sup>Asst.Prof. (Ece), Bhagwant University Ajmer & 07597730006

## ABSTRACT

*The thesis focuses on the application of computational intelligence (CI) techniques for two problems- System identification and digital filter design. In system identification, different case studies have been carried out with equal or reduced number of orders as the original system and also in identifying a blackbox model. Lowpass, Highpass, Bandpass, stopband FIR and Lowpass IIR filters have been designed using three algorithms. Using two different fitness functions. Particle Swarm Optimization (PSO), Differential Evolution based PSO (DEPSO) and PSO with Quantum Infusion (PSO-QI) algorithms have been applied in this work. PSO-QI is a new Hybrid algorithm where the global best particle obtained from PSO goes into a tournament with an offspring produced by mutating the global best of PSO using the quantum principle in quantum behaved PSO (QPSO) and the winner is selected as the new global best of the swarm.*

*In QPSO, unlike traditional PSO, exact values of particle's position and velocity cannot be determined. However, its position in the solution space is determined by mapping the probability of its appearance in the quantized search space. The results obtained from PSO-QI have been compared with the DEPSO hybrid algorithm and the classical PSO. In all of the cases, PSO-QI has outperformed the other two algorithms in its ability to converge to the lowest error value and its consistency in finding the solution every time and thus proven to be the best. However, the computational complexity of PSO-QI is higher than that of the other two algorithms.*

## I. INTRODUCTION

System identification is a challenging and complex optimization problem due to nonlinearity of systems and even more in a dynamic environment. Adaptive infinite impulse response (IIR) systems are preferably used in modeling real world systems because of their reduced number of coefficients and better response over the finite impulse response (FIR) filters. In this work, system identification has been viewed as a problem of adaptive IIR filtering so that it becomes a parameter estimation problem.

Digital filter design is also a complex optimization problem due to the number of filter parameters that can be optimized. Hence CI techniques can be used to estimate the filter coefficients so as to optimize these parameters and design the desired filter response.

PSO and its other variants have been a topic of research over the past decade. Inspired by social behavior of bird flocking and fish schooling, PSO has proven to be an effective stochastic search technique. Hence it has been applied to a wide variety of problems related to search optimization, clustering, routing, scheduling. PSO has gone through various changes and different variants have been introduced in order to solve the problem more effectively. It has also been combined with other different algorithms to create hybrid optimization algorithms. These algorithms have been reported in different literatures and applied to different practical applications. In this thesis, two problems have been studied – system identification and digital filter design. These applications have been implemented using the standard PSO and two hybrid algorithms – differential evolution particle swarm optimization (DEPSO) and PSO with quantum infusion (PSO-QI). These results of system identification have also been compared with another hybrid algorithm PSO with evolutionary algorithm (PSO-EA). The thesis covers the details of these algorithms, the research work carried out towards the implementation of the above mentioned problems and their results.

## **II. OBJECTIVES**

The main objective of this research is to apply swarm, evolutionary and quantum based algorithms to solve two practical problems viz. system identification and digital filter design. PSO, DEPSO and PSO-QI are the major algorithms involved in this work for system identification and in the design of digital filters. The results of the case studies are also presented

## **III. THESIS LAYOUT**

The thesis has been divided into 9 chapters. Chapter 1 introduces to the topic and Major areas of this research work. In Chapter 2, system identification has been explained This chapter introduces to the problem of system identification and traditional and modern techniques used to solve it. In Chapter 3, digital filter design is explained. This chapter introduces to the problem and traditional and modern techniques used in digital filter design In next three chapters, the three algorithms have been explained in detail. In Chapter 4, PSO has been covered. This chapter explains the basics of the algorithm and how it has been applied to the above mentioned problems. In Chapter 5, DEPSO has been explained. Similarly, PSO-QI has been explained in Chapter 6 In the next two chapters, case studies carried out during the research and the results obtained from them have been presented. In Chapter 7, studies and results of system identification have been presented. This chapter shows the comparison of results obtained from system identification, and is presented as figures and tabulated data. In Chapter 8, similar results obtained for digital filter design are presented. These results are also presented as figures and tabulated data and show a comparison of different algorithms as applied to the problem. Conclusion of the thesis and future work is presented

## **SYSTEM IDENTIFICATION**

### **INTRODUCTION**

System identification is a challenging and complex optimization problem due to nonlinearity of the systems and even more in a dynamic environment. Adaptive infinite impulse response systems are preferably used in modeling real world systems because of their reduced number of coefficients and better performance over the finite impulse response filters. Particle Swarm Optimization (PSO) and its other variants has been a subject of research for the past few decades for solving complex optimization problems. In this thesis, the concept of Differential Evolution based Particle Swarm Optimization (DEPSO) is implemented for system identification. A hybrid of Particle Swarm Optimization and Evolutionary Algorithm (PSO-EA) has been considered for comparison with PSO and DEPSO algorithms.

### **SYSTEM IDENTIFICATION PROBLEM**

System identification is the mathematical modeling of an unknown system by monitoring its input output data. This is achieved by varying the parameters of the enveloped model so that for a set of given inputs, its output match that of the system under consideration. For a plant whose behavior is not known, an adaptive system can be modeled and its parameters can be continuously adjusted using any adaptive algorithms. By the use of such adaptive algorithms, the required parameters can be obtained such that the output of the plant and the model are same for the same set of inputs, which is the goal of system identification (Panda et al., 2007). Traditionally, Least Mean Square(LMS) and other algorithms have been studied for the identification of linear and static systems (Windrow et. al., 1976). But, almost all physical systems are nonlinear to certain extent and recursive in nature and hence it is more convincing to model such systems by using nonlinear models (Panda et. al., 2007; Krusienski and Jenkins, 2005). Thus nonlinear system identification has attracted attention in the field of science and engineering. Hence these are better modeled as Infinite Impulse Response (IIR) models as they can provide better performance than a Finite Impulse Response (FIR) filter with the same number of coefficients (Shynk, 1989(a)). Thus the problem of nonlinear system identification can also be viewed as a problem of adaptive IIR filtering. Also, IIR models are more efficient than the FIR models for implementation as they require less parameter and hence fewer computations for the same level of performance. However, there are few problems associated with the use of IIR models in identification of a system, such as instability of the algorithms, slow convergence and convergence to the local minimum(Netto et al., 1995). In order to overcome these, different techniques have been developed over the years. Fig. shows a block diagram describing the problem of system identification.

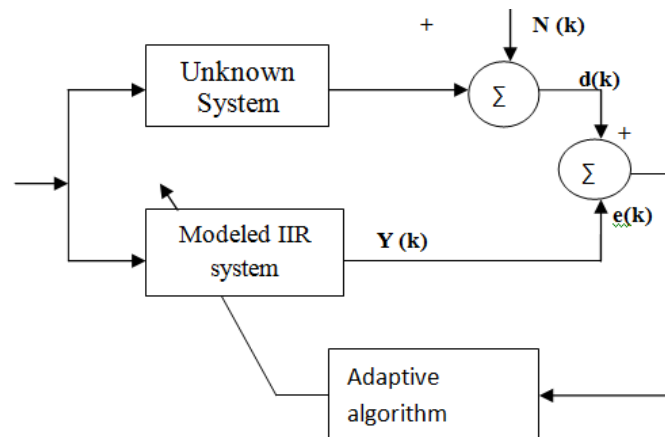


Figure.: Schematic showing system identification

### SYSTEM IDENTIFICATION TECHNIQUES

Different learning algorithms have been used in the past for nonlinear system identification. These techniques include use of neural network (Hongwei and Yanchun, 2005) and gradient based search techniques such as least mean square algorithm (Shynk, 1989(a)). Unfortunately, the error surface of such recursive systems such as a multi-machine power system (Kundur, 1993) tends to be multi-modal and hence traditional techniques of parameter approximation fail as they get trapped into local minimum and cannot attain the global minimum (Krusiensi and Jenkins, 2005). Various algorithms that are implemented in the adaptive IIR filtering for system identification are described in (Netto et al., 1995).

Population based search algorithm such as Genetic Algorithm (GA) has also been used for the system identification. It uses a population of potential solutions encoded as chromosomes which go through genetic operations such as crossover and mutation to find the best solution (Kristinsson and Dumont, 1992). But its effectiveness is affected by the convergence time (the time it takes to find the global minimum). So to eliminate such inefficiencies, population based stochastic optimization techniques have been discussed in various literatures. Particle Swarm Optimization (PSO) is one of the most known techniques (delValle et al., 2007). Application of PSO in the system identification has been discussed in (Panda et al., 2007). In (Lee et al., 2006), a method for the identification of nonlinear system and parameter optimization of the obtained input-output model has been described. The proposed method uses least squares support vector machines regression based on PSO. In another work, PSO has been used for optimizing the parameters of Elman neural network which is used for speed identification of ultrasonic motors (Hongwei and Yanchun, 2005). A modified form of PSO called as the self-organizing particle swarm optimization and its application in the system identification has been discussed in (Shen and Zeng, 2007). Radial Basis Function Neural Network (RBFNN) has been used for system identification in (Chen et al., 2007), where a hybrid gradient-based PSO algorithm has been used to adjust the parameters of the RBFNN. In (Liu et al., 2006), particle swarm optimization and quantum-behaved particle swarm optimization have been used for the system identification. Use of different types of stochastic optimization techniques in adaptive IIR filters and nonlinear systems has been explained in (Krusiensi and Jenkins, 2005). Use of Differential Evolution (DE) and Ant Colony Optimization (ACO) in IIR filter design has been presented in (Karaboga, 2005) and (Karaboga et al., 2004) respectively. They also talk about the possible use of these approaches in system identification and other applications. But these algorithms have the tendency to get stuck in the local minimum when the complexity of the problem increases and in dynamic systems where time allowed for convergence is constrained. Hybrid algorithms are used to improve the performance by combining the best feature of both algorithms. In (Cai et al., 2007), one such hybrid algorithm has been shown. In the paper, PSO and Evolutionary Algorithm (PSO-EA) hybrid has been implemented to combine the best features of PSO (co-operation) and EA (competition).

### SUMMARY

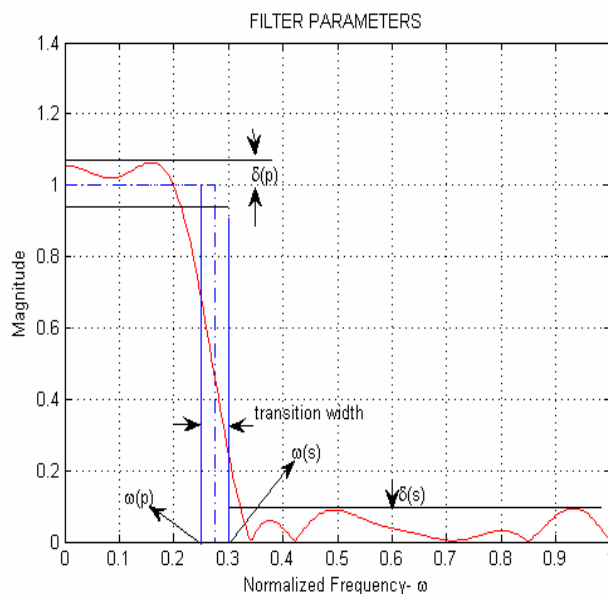
Identification of complex systems is an optimization problem and is viewed as IIR system identification in this chapter. By the use of swarm and evolutionary algorithms, the coefficients of the filter are determined. The results of the study are shown in Chapter

**DIGITAL FILTER DESIGN  
INTRODUCTION**

This chapter introduces digital filter design as an optimization problem and discusses various methods applied in the design of digital filters traditionally and currently using the computational intelligence techniques.

**DIGITAL FILTER**

A filter is a frequency selective circuit that allows a certain frequency to pass while attenuating the others. Filters could be analog or digital. Analog filters use electronic components such as resistor, capacitor, transistor etc. to perform the filtering operations. These are mostly used in communication for noise reduction, video/audio signal enhancement etc. In contrast, digital filters use digital processors which perform mathematical calculations on the sampled values of the signal in order to perform the filter operation. A computer or a dedicated digital signal processor may be used for implementing digital filters. Filters mostly find their use in communication for noise reduction, audio/video signal enhancement etc. Any time varying signal  $C=x(t)$  sampled at a sampling interval of  $h$  has input signals  $X_0, X_1, X_2, \dots$  in intervals  $0, h, 2h, 3h, \dots, nh$ . These inputs have corresponding outputs  $y_0, y_1, y_2 \dots y_n$ , depending upon the kind of operation performed. Thus, the order of the filter is determined by the number of the previous input terms used to calculate the current output. The  $a_0, a_1, a_2$  terms appearing in the following equations are called the filter coefficients and determine the operation of the filter. These determine the characteristics of the filter. Various filter parameters which come into picture are the stopband and passband normalized frequencies ( $\omega_s, \omega_p$ ) the passband and stopband ripple ( $\delta_p$ ) and ( $\delta_s$ ) the stopband attenuation and the transition width. This has been shown in Fig.



**PARTICLE SWARM OPTIMIZATION**

**INTRODUCTION**

Introduced by Eberhart and Kennedy in 1995 (del Valle et al., 2007), PSO is a search technique based on social behavior of bird flocking and fish schooling. There are different kinds of bio and social behavior inspired algorithms. PSO is one of the different swarm based algorithms. In PSO, each particle of the swarm is a possible solution in the multi-dimensional search space. The particles change their positions with a certain velocity in each iteration, according to the standard PSO equations, thus moving towards the global best (gbest) solution. Being easy to implement and yet so effective, PSO has been utilized in a wide variety of optimization applications. In this thesis, PSO has been used in system identification and to design digital filters.

### PSO ALGORITHM

Particle swarm optimization is a population based search algorithm and is inspired by the observation of natural habits of bird flocking and fish schooling. In PSO, a swarm of particles moves through a D dimensional search space. The particles in the search process are the potential solutions, which move around the defined search space with some velocity until the error is minimized or the solution is reached, as decided by the fitness function. Fitness function is the measure of particles fitness which is the deviation of the particle from the required solution. The particles reach to the desired solution by updating their position and velocity according to the PSO equations. In PSO model, each individual is treated as a volume-less particle in the D - dimensional search space with initial random velocity. Each particle has memory which keeps track of its previous best position and fitness, with the position and velocity of i particle represented as:

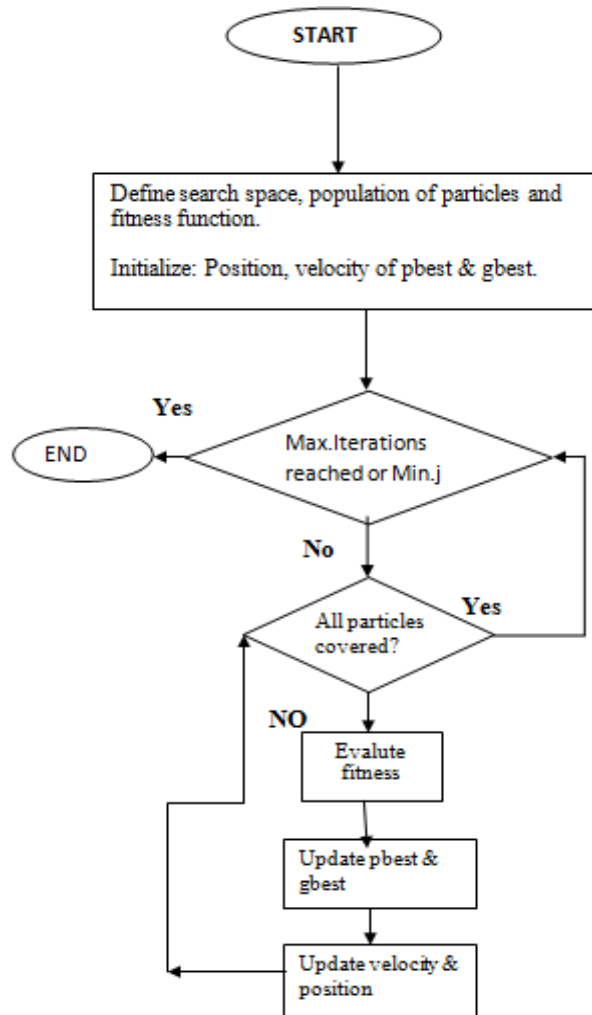


Fig: Flowchart for PSO

### DIFFERENTIAL EVOLUTION PARTICLE SWARM OPTIMIZATION INTRODUCTION

Due to the limitations of PSO in finding the best solution, different other approaches were also considered. Over the past few years, research in the field of computational intelligence gave birth to a number of different approaches. All of these algorithms had some special features in finding the best solutions, either their convergence speed or their ability to find the better solution. However, they suffered from one or the other problems. In order to overcome these shortcomings and utilize their effective best properties, hybrid algorithms were introduced. Hybrid algorithms take the best features of the individual algorithms and thus tend to be more effective than the individual algorithms. DEPSO is one of such hybrid algorithms. In this chapter, DEPSO and its applications in system identification and digital filter design is discussed.

## **DEPSO ALGORITHM**

DEPSO is the hybrid of DE and PSO. Differential Evolution. Differential Evolution was introduced by Storn and Price in 1995 (Storn, 1996). It is also a population based stochastic search technique for function minimization. In (Storn, 1996), DE has been applied in the field of filter design. In DE, the weighted difference between the two population vectors is added to a third vector and optimized using selection, crossover and mutation operators as in to a third vector and optimized using selection, crossover and mutation operators as in individual, called the offspring, is then recombined with the parent under certain criteria such as crossover rate. Fitness of both the parent and the offspring is then calculated and the offspring is selected for the next generation only if it has a better fitness than the parent (Karaboga, 2005). The mutation takes place according to (14).

## **CONCLUSION INTRODUCTION**

In this work, swarm, evolutionary and quantum based intelligent optimization algorithms are used in system identification and to design digital filters. It was shown that the swarm based algorithms has many variants and has been hybridized with other algorithms to increase its effectiveness. It was also seen that by hybridization of the algorithms, best features of both the algorithms are retained and thus new algorithm so developed is more robust. In this chapter, a conclusion of all the chapters is provided.

## **SECTION SUMMARY**

The first three chapters of the thesis cover the introduction to the problem. In Chapter 1, introduction to the thesis is provided. Chapter 2 covers the description of system identification. Introduction to the problem and traditional and modern methods applied to solve it are explained in this chapter. In Chapter 3, digital filter design is explained. This chapter also introduces to the problem of digital filter design and various traditional and new methods applied in the design. The next three chapters of the thesis describe the involved algorithms and their operation in detail. In Chapter 4, particle swarm optimization has been explained. As one of the pioneer stochastic search optimization technique based on the social behavior of bird flocking and fish schooling, algorithm of PSO has been described in this chapter. In Chapter 5, a hybrid optimization algorithm DEPSO has been explained. A combination of DE and PSO, it uses the differential evolution operation on the particle of the PSO to mutate the particle and create an offspring. The chapter covers the detail of its operation. In Chapter 6, another hybrid algorithm, PSO-QI has been introduced. PSO-QI emerges from the infusion of quantum operation obtained from QPSO on the particle of the PSO. Concepts of quantum particle swarm optimization and its application on the PSO have been explained in this chapter. In the next two chapters, the results obtained from the case studies have been presented. In Chapter 7, the results obtained from the application of different algorithms in the system identification have been presented. These results show the effectiveness of the new hybrid algorithms in comparison to the traditional PSO. In Chapter 8, the results for the digital filter design are shown. This chapter shows the results of designing different kinds of digital filters using various algorithms described in the previous chapters. These results also suggest that the new hybrid algorithms are more effective than the traditional PSO. These two chapters present their comparison in terms of figures and tabulated data from different case studies.

## **MAIN CONCLUSION**

The main focus of the thesis is in system identification and in the design of digital filters. The research work leading to the thesis is related to identification of an IIR system. This is achieved by modeling the unknown system with IIR systems of same or reduced number of orders. In digital filter design, Lowpass, Highpass, Bandpass and Bandstop FIR and Lowpass IIR filters are designed using different optimization algorithms. The results for system identification as well as digital filter design have been shown. In this work, particle swarm optimization is used as the baseline algorithm. Two other algorithms are considered to improve the results obtained from PSO. These are hybrid algorithms based on differential evolution and quantum particle. The DEPSO algorithm performed better than PSO in system identification as well as in digital filter design. Results obtained from PSO-QI are better than both PSO and DEPSO and hence it has outperformed the other two algorithms in all the case studies of system identification and digital filter design.

Fitness function based on passband and stopband ripples of the filter response is used to design both FIR and IIR filters whereas the fitness function based on MSE is used to design FIR filters only. It is observed that all three of the algorithms are able to approximate the filter coefficients in a number of iterations but PSO-QI always performed the best among them. Figures and tabulated results all show that PSO-QI is more consistent in its performance and it can achieve a lower value of average error in the cases using two different fitness functions. Although it took longer for the algorithm to converge because of its computational complexity, it found much better solution than PSO, DEPSO and QPSO. The results are not tabulated for QPSO because of the higher number of iterations and the results are clear from the figures. However, comparison has been made to confirm that PSO can not achieve the same amount of convergence even when allowed to run for the amount of time taken by PSO-QI. Hence, it can be concluded that swarm, evolutionary and quantum algorithms can be effectively used in digital filter design, and PSO-QI is a better choice. It is evident from the figures and results how the best features of two algorithms can be extracted and performance can be improved by the hybridization of these algorithms.

## **FUTURE RESEARCH**

This thesis covered application of different optimization algorithms in system identification and digital filter design problems. However, there is more room for research. The most open ground for research is the improvement of the algorithms themselves. The parameters tuning is a big issue in the use of these algorithms and efforts are being made to reduce the number of parameters that determine the effectiveness of the algorithm. Apart from that, the hybrid algorithms leave a lot of room for research in how the hybridization should be carried out. In some cases, the gbest particle obtained from PSO is used; where as the whole population is mutated in other cases. The mutation operation is sometime applied to a random member of the pbest population where as sometimes on the gbest particle itself.

These different choices affect the effectiveness of the algorithms differently and no fixed convention has been defined. It is up to the researcher to decide and apply his intuition and experience based on trail and error over a number of trials. Thus exploration of these areas in improving the effectiveness of the algorithms based on the best parameters and best approach to hybridization remains to be a work for future research.

In this thesis, a quantum behaved particle swarm optimization was introduced those concepts are radical to the classical concept of swarm optimization. However, it as shown that these algorithms are more effective than the classical PSO. So, it is also a round for future research how new algorithms can be developed by borrowing concepts from different fields of science and applied to improve the existing algorithms. Apart from that, the application of these and other various algorithms in other different kinds of real world applications also remains to be the work for future research This research mainly focused on carrying out simulations on the computer using. So, its implementation on a dedicated digital signal processor (DSP) on real ata can also be looked at in the future. By implementing the digital filters on a DSP with actual data from various sources such as power systems, the ability of the algorithms to actually identify the filter coefficients and design adaptive filters could be tested. On a hardware environment, various other constraints such as memory, storage size, speed of the processor etc. will also come into the effect and hence design of algorithms according to these requirements will pose more challenge to the research.

## **SUMMARY**

In this chapter, summary of all the chapters was covered. The chapter covered the ain motivation of the thesis and briefly summarized how different algorithms are used in two different kinds of optimization problems in the research work. The chapter also concluded that the hybrid algorithms have given better results and also explained the remaining work that can be taken forward for the future research.

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