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## An Efficient Adaptive System Identification Technique Based on Wind Driven Optimization Method

#### Rashmi Sinha\*, Arvind Choubey and Santosh Kumar Mahto

Department of Electronics and Communication Engineering, National Institute of Technology, Jamshedpur, India. Email: rsinha.ece@nitjsr.ac.in, achoubey.ece@nitjsr.ac.in, ec51236@nitjsr.ac.in

#### **Abstract**

**Objectives:** This paper presents a novel methodology for estimating the parameters of an unknown system or a plant using Wind Driven Optimization (WDO) based adaptive identification model. **Methods/Statistical Analysis:** Significant endeavours are being made by researchers in the field of system identification towards building an adaptive identification model which can approximately track the plant dynamics. This work introduces the application of one of the most recently developed nature inspired WDO algorithm in system identification task. **Findings:** The performance of the introduced WDO based system identification technique is compared with few popular algorithms such as Least Mean Square (LMS), Bacteria Foraging Optimization (BFO), and Genetic Algorithm (GA). WDO based model is implemented for two sets of experiments at 10dB and 30dB signal to noise ratio. Normalised Mean Square Error (NMSE) obtained by the presented method at 10dB is as low as -14.71dB at 38 iterations as compared to -10.69dB at 350 iterations, -9.526dB at 192 iterations and -8.99dB at 18 iterations for LMS, BFO and GA based methods respectively. When Signal to Noise Ratio (SNR) considered is 30dB, NMSE obtained by WDO is -33.74dB at 14 iterations which is better than -30.15dB at 328 iterations, -28.66dB at 193 iterations and -28.09dB at 30 iterations for LMS, BFO and GA based methods respectively. The obtained results exhibit a very promising capability of WDO in tracking the unknown system parameters. **Application/Improvements:** The proposed adaptive identification model can be widely used in instrumentation, acoustic noise and vibration control, power system, telecommunication, adaptive guidance or fault tolerance etc.

**Keywords:** Signal to Noise Ratio, System Identification, Wind Driven Optimization

### 1. Introduction

System identification is a major concern in industrial control, automation, and intelligent instrumentation and communication system areas because it is difficult to obtain effective solutions for these nonlinear dynamic systems. The problem is more aggravated when stricter design criteria has to be satisfied with no or negligible a priori knowledge of the system. It aims at estimating the parameter vector of the mathematical model that aptly describes the dynamics of the unknown system (also referred as plant) under consideration. A great benefit of identification, seldom acknowledged, is its ability to

uncover shortcomings and anomalies of an unknown system by observing its input-output relation and to inspect intelligent means for controlling it<sup>1</sup>. It finds extensive applications in instrumentation, control, acoustic noise and vibration control, power system, telecommunication, adaptive guidance or fault tolerance etc<sup>2-3</sup>. The task of the identification algorithm is to adapt itself to track the varying system dynamics of the plant appropriately. It will not be an exaggeration if we say that the topic of system identification is the accurate estimation of the parameters of the plant which, otherwise, is not possible in real world.

Existing literature has rich articles on methods for identification of unknown system parameters based

<sup>\*</sup>Author for correspondence

on the synchronized outcomes of the predictions of mathematical and experimental models, as briefed up in the following write up. Filters dependent on stochastic gradient algorithms play a vital role in numerous applications of adaptive signal processing including system identification 4-6. The LMS algorithm has been a popular choice, as an adaptive algorithm, owing to its simplicity and stability. But, its performance seriously degrades in non-linear scenario, especially when corrupted with heavy tailored or impulsive noise<sup>7-9</sup>. Recent trends in identification of complex non-linear dynamic plants are to employ a non-linear model and optimize their parameters by nature inspired evolutionary computing tools 10-21. These optimization techniques focus at enhancing the chances of encountering the global optimum, without going through in-depth search of the whole parameter space. They do not depend on filter structure like gradient-based techniques and therefore, are effective in optimizing the parameters of identification model irrespective of its structure. These optimized parameters can represent any possible parameters of the unknown system model until some minimal error condition is satisfied. Multi-Layer Perception (MLP) is one of the first one to be reported in literature 10. Later a new approach was proposed by employing a low complexity Functional Link Artificial Neural Network (FLANN) for better performance<sup>13</sup>. However, the major disadvantage of these derivative based learning rules is that at times it may give local minima and thus misleading guess of the parameters. So, focus turned to derivative free heuristic optimization techniques such as Particle Swarm Optimization (PSO)<sup>14-16</sup>, GA<sup>17-20</sup>, Artificial Immune System (AIS)11, BFO21 etc. Each algorithm has its own merits and demerits. GA takes excessively large search time even though it is efficient in finding global minimum. PSO is better than GA when it comes to convergence speed but at times it gets captivated in local optima when dealing with some complex or multimodal functions<sup>15</sup>. Each one of them has its strengths and weaknesses. It is a mathematically proven fact that no method can be singled out as the best method for solving all types of problems<sup>22</sup>. These algorithms have long been employed for system identification problem with varying degree of success.

Encouraged by the drawbacks of above evolutionary optimization algorithms, we attempt to investigate the feasibility and performance of WDO based identification model to identify the unknown system parameters having familiar plant structure<sup>23-26</sup>. The inspiration of WDO

is drawn from atmospheric motion of extremely small air parcel guided by Newton's second law of motion. This methodology provides robustness and extra degree of freedom to fine tune because of the new terms i.e. gravitational and Coriolis forces incorporated in its velocity update equation. Therefore, this approach seems to be more hopeful and promising alternative to some of the popular evolutionary algorithms such as PSO<sup>14-16</sup> and GA<sup>17-20</sup>. It has already been satisfactorily applied to solve optimization tasks in area of antenna design<sup>23-26</sup>.

Rest of the paper is organised as follows. In section 2, fundamental principle of system identification using adaptive FIR filter as identification model is described. The basic WDO algorithm and its implementation to develop adaptive identification model is dealt with in section 3. Exhaustive simulation is performed to explore the viability of the presented approach in section 4. Final section 5 contains conclusion and future scopes.

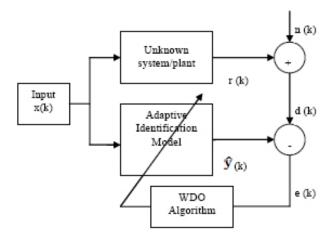
## 2. System Identification

An unknown plant whose behaviour is unpredictable may be modelled appropriately based upon existing structure and then identification of its parameters can be accomplished through associated optimization algorithm such as GA, BFO, and PSO etc. A suitable model structure should be selected after acquiring the data. Several model structures Finite Impulse Response (FIR), Infinite Impulse Response (IIR), MLP, and FLANN etc. are accessible to assist in modelling a system. A prior knowledge is usually exploited to determine the structure of model. In the absence of a priori knowledge, trial and error method may be adopted to realize the model structure. Mathematical representation of system model under study is the primary concern of system identification problem.

The block diagram of system identification scheme is shown in Figure 1. As illustrated in the figure, the input given to an unknown plant and the adaptive identification model is a uniformly distributed random signal x(k), resulting in output signals r(k) and  $\hat{y}(k)$  respectively.

## 2.1 Unknown System (Plant) Model

The plant model considered in this section is an adaptive FIR filter with fixed multiplier referred as coefficient or weight of filter. This linear combiner structure<sup>4</sup> is shown in Figure 2. The input vector is represented by  $\mathbf{x}(\mathbf{k}) = [\mathbf{x}(\mathbf{k}), \mathbf{x}(\mathbf{k} - \mathbf{1}) \dots \mathbf{x}(\mathbf{k} - \mathbf{N} + \mathbf{1})]^T$ 



**Figure 1.** Schematic block diagram of WDO based adaptive system identification

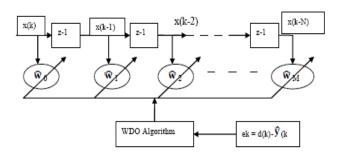


Figure 2. FIR structure of adaptive identification model

and the weight vectors of the FIR filter structure by  $\mathbf{w}(\mathbf{k}) = [\mathbf{w0}(\mathbf{k}), \mathbf{w1}(\mathbf{k}), \dots \mathbf{wM} - \mathbf{1}(\mathbf{k})]^T$  at the  $k^{th}$  iteration. The number of input samples is N and M is the length of the filter. The  $k^{th}$  output is then given by:

$$\mathbf{r}(\mathbf{k}) = \sum_{n=0}^{N-1} \mathbf{w}_{k} \mathbf{x}(n - \mathbf{k}) = \mathbf{w}^{T}(\mathbf{k}) \mathbf{x}(\mathbf{k})$$
(1)

The output of the plant is distorted due to the presence of noise n(k), mostly additive white Gaussian noise (AWGN). Therefore, the desired signal must include n(k) and can be expressed as:

$$\mathbf{d}(\mathbf{k}) = \mathbf{r}(\mathbf{k}) + \mathbf{n}(\mathbf{k}) \tag{2}$$

#### 2.2 Identification Model

Same adaptive FIR filter described in preceding section is considered as system identification model. The only difference is that, instead of fixed weights, the weights of filter are optimized by WDO algorithm, in this case. Weights are initialized to any random values

at the beginning of the algorithm and then updated subsequently by WDO technique. The weights of the assumed FIR filter model is represented by  $\widehat{\mathbf{w}}(\mathbf{k}) = \left[\widehat{\mathbf{w}0}(\mathbf{k}), \widehat{\mathbf{w}1}(\mathbf{k}), \dots, \widehat{\mathbf{w}N} - \mathbf{1}(\mathbf{k})\right]^T$ , which has the same length as  $\mathbf{w}(\mathbf{k})$ . Output at the  $\mathbf{k}^{th}$  instant is given by:

$$\widehat{\mathbf{y}}(\mathbf{k}) = \sum_{n=0}^{N-1} \mathbf{w}_{\mathbf{k}} \mathbf{x}(n - \mathbf{k}) = \widehat{\mathbf{w}}^{T}(\mathbf{k}) \mathbf{x}(\mathbf{k})$$
(3)

Henceforth, the goal of system identification is to estimate  $\mathbf{w}(\mathbf{k})$  using  $\widehat{\mathbf{w}}(\mathbf{k})$ . In practice, however, due to the existence of AWGN and meagre knowledge of  $E\{x(\mathbf{k})\}$  and  $E\{d(\mathbf{k})x(\mathbf{k})\}$ , misalignment between  $\mathbf{w}(\mathbf{k})$  and  $\mathbf{w}(\mathbf{k})$  occurs<sup>4</sup>. The mean square error (MSE) between the desired and estimated output acts as an acceptable cost/ objective function and is given by:

$$MSE(k) = \frac{1}{N} \sum_{k=0}^{N} e_k^2$$
 (4)

where  $\mathbf{e_k} = \mathbf{d(k)} - \hat{\mathbf{y(k)}}$  the cost function is instrumental in speculating the efficacy of the identification model carved on some optimization algorithm.

## 3. Adaptation of Wind Driven Optimization Algorithm for System Identification Problem

#### 3.1 WDO Principle

WDO technique is a recently developed nature-inspired evolutionary algorithm, which is getting much acclaim due to its good exploration and diversity properties<sup>23-24</sup>. It belongs to a class of swarm intelligence technique where the air parcel in the earth's atmosphere have deliberate and pointed movement towards an optimum air pressure location in an attempt to balance the horizontal pressure of the air parcel. The population of air parcels travel within the search space randomly bounded in [-1, 1]. The velocity and position of each air parcel is updated similar to the particles of PSO technique every iteration. This iterative process continues till the air parcels achieve optimum pressure location to provide the optimum solution. Gravitation and Coriolis forces present in the velocity update equation makes the algorithm robust and also adds extra flexibility to fine tune. This algorithm is found to be superior to some well- known soft computing techniques such as PSO, GA, and comprehensive learning particle swarm optimization (CLPSO)<sup>16</sup>. It has been found to be an effective technique in improving the performance of some established algorithms such as Invasive Weed Optimization (IWO)<sup>26</sup>.

Four basic forces acting on the air parcels that causes them to move in a specified direction at a particular velocity or forces that deviates it from its current path are pressure gradient force, friction force, gravitational force and Coriolis force caused due to earth's rotation. A set of air parcel occupies random positions in the search space initially and are assigned random velocities. As the parcels drift towards an optimum pressure location, their velocity and position are updated every iteration using following update equations<sup>23</sup>

$$\mathbf{u}_{\text{new}} = (\mathbf{1} - \alpha)\mathbf{u}_{\text{cur}} - \mathbf{g}\mathbf{x}_{\text{cur}} + \left(RT \left| \frac{1}{i} - 1 \right| \left(\mathbf{x}_{\text{opt}} - \mathbf{x}_{\text{cur}}\right)\right) + \frac{\mathbf{c}\mathbf{u}_{\text{cur}}^{\text{otherdim}}}{i} \quad (5)$$

$$\mathbf{x}_{\text{new}} = \mathbf{x}_{\text{cur}} + \mathbf{u}_{\text{new}} \Delta t$$
 (6)

where  $\mathbf{u}_{\text{new}}$  is the velocity of air parcel in the next iteration, the velocity at the current iteration is denoted by  $\mathbf{u}_{\text{cur}}$ ,  $\alpha$  and g being friction coefficient and gravitational constant respectively,  $\mathbf{x}_{\text{cur}}$  is the current location where as  $\mathbf{x}_{\text{new}}$  is the new position of air parcel, RT defines universal gas constant and temperature, C is the Coriolis force,  $\mathbf{x}_{\text{opt}}$  being the optimum location and  $\mathbf{cu}_{\text{cur}}^{\text{otherdim}}$  is the substituted velocity vector chosen from different random dimension representing the influence of Coriolis force. Assume time step,  $\Delta t$  equal to 1. The magnitude of the velocity is restricted by following condition, whenever it exceeds the threshold value in whatsoever dimension

$$\mathbf{u}_{\text{new}}^* = \begin{cases} \mathbf{u}_{\text{max}} & if \ \mathbf{u}_{new} > \mathbf{u}_{\text{max}} \\ -\mathbf{u}_{\text{max}} & if \ \mathbf{u}_{new} < -\mathbf{u}_{\text{max}} \end{cases}$$
(7)

where  $u_{\text{new}}^*$  is the limited velocity and  $|u_{\text{max}}|$  is the maximum threshold speed in preserved direction of motion.

The flowchart of WDO is illustrated in Figure 3.

# 3.2 Weight Update of Adaptive FIR Filter using WDO Algorithm

The unknown system or plant is connected in parallel to the proposed WDO based adaptive model, as illustrated in the above section. Unknown system is modelled as a fixed FIR filters and the adaptive model taken is an FIR filter too but with random weights. The objective of the aforesaid methodology is to adjust the filter weight so as to minimize the objective/cost function, MSE given

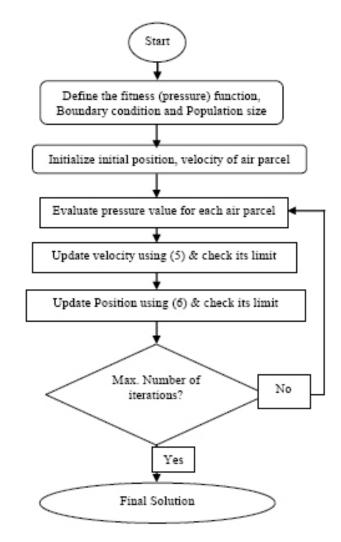


Figure 3. Flow chart of WDO algorithm

by (4). The training rule for the weight update of WDO based model is enumerated in the following steps.

- Step 1: A group of R (= 40) number of air parcels each represented by M unknown parameters which are to be optimized (coefficients,  $\widehat{\boldsymbol{w}}_{j}(k)$  of the adaptive identification model, in this case), are initialized. Each air parcel represents potential candidate solution.
- Step 2: Uniformly distributed random signal in the interval [-1, 1] and having unity variance is generated and fed to the plant and WDO based identification model simultaneously.
- Step 3: Desired signal is the resultant signal obtained by feeding the input samples to the plant and contaminating its output with measured additive noise i.e. k numbers of desired samples are produced.

- Step 4: Desired output sample is compared with the corresponding output of the identification model. Therefore, k number of errors is produced for R number of air parcels, in all.
- Step 5: The fitness of air parcel is evaluated at each epoch according to (4).
- Step 6: Each air parcel is ranked in ascending order of their fitness function value and the most fit air parcel (minimum MSE) is progressively stored which manifests the learning characteristics of the adaptive model.
- Step 7: The velocity of each air parcel is updated according to (5) and (7). The position is updated using (6).
- Step 8: When minimum MSE reaches the pre-specified level or maximum number of iterations, the recursive process stops.

## 4. Simulation Results and Discussions

The performance of the proposed WDO based equalizer is assessed through extensive simulation carried out on two sets of experiments 1 and 2 as indicated in Table 1. AWGN is added to the output of the unknown plant to generate the desired signal, which in our case is the communication channel modelled on FIR filter<sup>27</sup>. This is depicted in Figure 1. Two sets of linear channel model (CH1 and CH2) are considered and two nonlinear functions (NL1 and NL2) are incorporated to convert the channel into nonlinear system. One thousand input samples are fed to train weights for 500 iterations. Population of air parcel corresponding to system parameters is taken

Table 1. Problem specification

| Channel                              | Experiment 1 CH1:<br>0.3040 + 0.9029 z <sup>-1</sup><br>+ 0.3040 z <sup>-2</sup> | Experiment 2 CH2:<br>0.2600 + 0.9300 z <sup>-1</sup><br>+ 0.2600 z <sup>-2</sup> |  |  |  |
|--------------------------------------|--|--|--|--|--|
| Linear system (channel) model,       | CH1NL0   | CH2NL0   |  |  |  |
| Non-linear metans                    | CH1NL1 NL1: tanh<br>(r(k))   | CH2NL1 NL1: tanh<br>(r(k))   |  |  |  |
| Non-linear system<br>(channel) model | CH1NL2 NL2: r(k)<br>+ 0.2 r(k)^2 - 0.1<br>r(k)^3                                 | CH2NL2 NL2: r(k)<br>+ 0.2 r(k)^2 - 0.1<br>r(k)^3                                 |  |  |  |
| Length of channel                    | 3  |  |  |  |  |
| Signal to noise ratio (SNR)          | 10dB and 30dB  |  |  |  |  |

as 40. Other parameter values used in the simulation are recorded in Table 2.

The parameters of unknown system is tracked using WDO based adaptive FIR filter and the convergence characteristics obtained is compared with BFO, LMS and GA based system identification technique. The NMSE for the given specifications are illustrated in Figures 4-7 and numerical data of the results are illustrated in Table 3. The estimated plant parameters using WDO is compared with BFO, GA and LMS based methods under different noise conditions and non-linearity and is summarized in Table 4.

It can be seen from Figure 4 that for a linear channel at SNR equal to 10dB, NMSE as low as -14.71dB at 38 iterations is achieved using WDO as compared to -9.526dB at 192 iterations,-8.99dB at 31 iterations and -10.69dB at 184 iterations for BFO, GA and LMS respectively. Figure 6 shows that under low noise condition at 30dB, NMSE is further improved to -33.74dB at 14 iterations for WDO

Table 2. Parameters used for simulation

|     | Max. number of iterations, Iter <sub>m</sub> = 300 |  |  |  |
|-----|--|--|--|--|
|     | Constant, RT =1.5                                  |  |  |  |
|     | Gravitational constant, $g = 0.1$                  |  |  |  |
|     | Friction coefficient, $\alpha = 0.8$               |  |  |  |
| WDO | Coriolis constant, $c = 3.2$                       |  |  |  |
|     | Maximum allowed speed, $u_{max} = 0.3$             |  |  |  |
|     | Lower dimension boundary, dimMin = - 1             |  |  |  |
|     | Upper dimension boundary, dimMax = 1               |  |  |  |
|     | Population size = 40                               |  |  |  |
|     | Max. number of iterations =500                     |  |  |  |
| LMS | Number of input samples = 500                      |  |  |  |
|     | Step size = $0.2$                                  |  |  |  |
|     | No. of chromosomes = 60                            |  |  |  |
|     | No. of binary bits =50                             |  |  |  |
| GA  | No. of inputs samples = 500                        |  |  |  |
|     | Crossover probability = 0.85                       |  |  |  |
|     | Mutation Probability = 0.005                       |  |  |  |
|     | Number of bacteria =12                             |  |  |  |
|     | Probability of elimination and dispersal = 0.25    |  |  |  |
|     | Swimming length after which tumbling of bacteria   |  |  |  |
|     | will   |  |  |  |
| ВГО | be undertaken in a chemotactic loop = 7            |  |  |  |
|     | Number of iterations to be undertaken in a         |  |  |  |
|     | chemotactic loop =5                                |  |  |  |
|     | Maximum number of reproductions to be              |  |  |  |
|     | undertaken =30                                     |  |  |  |
|     | Maximum number of elimination and dispersal        |  |  |  |
|     | events to be                                       |  |  |  |
|     | imposed over the bacteria = 10                     |  |  |  |

Table 3. Comparative convergence plot

| Table 5. Comparative convergence plot |         |            |        |        |        |        |       |        |        |        |
|---------------------------------------|---------|------------|--------|--------|--------|--------|-------|--------|--------|--------|
|                                       | Channel |            | WDO    |        | BFO    |        | GA    |        | LMS    |        |
|                                       |         |            | SNR    | SNR    | SNR    | SNR    | SNR   | SNR    | SNR    | SNR    |
|                                       |         |            | 10dB   | 30dB   | 10dB   | 30dB   | 10dB  | 30dB   | 10dB   | 30dB   |
|                                       | CH1     | No. of     | 38     | 14     | 192    | 193    | 18    | 30     | 350    | 328    |
|                                       | NL0     | iterations |        |        |        |        |       |        |        |        |
|                                       |         | NMSE in    | -14.71 | -33.74 | -9.526 | -28.66 | -8.99 | -28.09 | -10.69 | -30.15 |
|                                       |         | dB         |        |        |        |        |       |        |        |        |
| ıt 1                                  | CH1     | No. of     | 30     | 48     | 234    | 218    | 12    | 32     | 320    | 472    |
| Experiment 1                          | NL1     | iterations |        |        |        |        |       |        |        |        |
| eri                                   |         | NMSE in    | -12.85 | -25.90 | -8.67  | -25.61 | -9.19 | -24.16 | -10.00 | -25.88 |
| Exp                                   |         | dB         |        |        |        |        |       |        |        |        |
|                                       | CH1     | No. of     | 19     | 57     | 230    | 242    | 19    | 17     | 280    | 253    |
|                                       | NL2     | iterations |        |        |        |        |       |        |        |        |
|                                       |         | NMSE in    | -13.81 | -20.20 | -8.79  | -19.76 | -8.77 | -18.89 | -9.76  | -20.30 |
|                                       |         | dB         |        |        |        |        |       |        |        |        |
|                                       | CH2     | No. of     | 49     | 35     | 239    | 216    | 12    | 28     | 323    | 323    |
|                                       | NL0     | iterations |        |        |        |        |       |        |        |        |
|                                       |         | NMSE in    | -14.54 | -33.60 | -9.489 | -29.00 | -8.15 | -27.28 | -10.25 | -29.83 |
| _                                     |         | dB         |        |        |        |        |       |        |        |        |
| Experiment 2                          | CH2     | No. of     | 31     | 27     | 228    | 200    | 24    | 22     | 257    | 268    |
| me                                    | NL1     | iterations |        |        |        |        |       |        |        |        |
| eri                                   |         | NMSE in    | -12.72 | -27.85 | -9.22  | -26.29 | -8.97 | -25.24 | -9.87  | -27.37 |
| Exi                                   |         | dB         |        |        |        |        |       |        |        |        |
|                                       | CH2     | No. of     | 58     | 49     | 240    | 213    | 9     | 17     | 316    | 257    |
|                                       | NL2     |            |        |        |        |        |       |        |        |        |
|                                       |         | NMSE in    | -11.86 | -20.93 | -9.22  | -20.21 | -8.58 | -18.75 | -10.14 | -20.56 |
|                                       |         | dB         |        |        |        |        |       |        |        |        |

as compared to -28.66dB at 193 iterations, -28.09dB at 30 iterations and -30.15dB at 328 iterations for BFO, GA and LMS respectively.

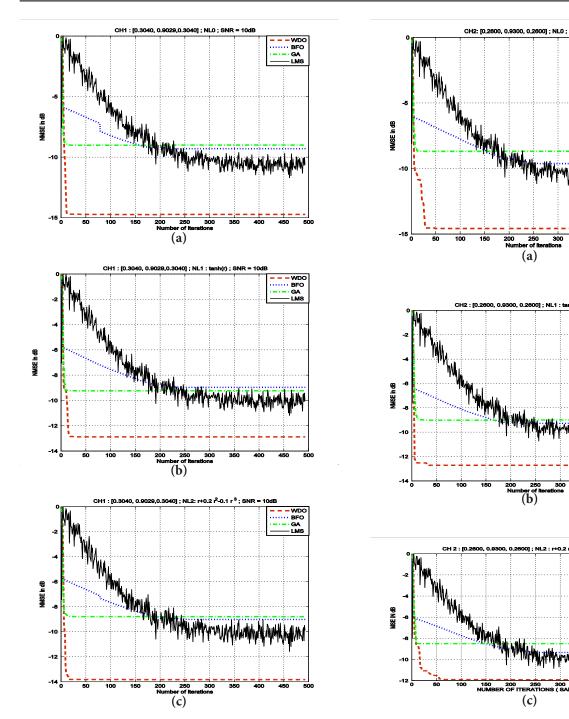
For non-linear channel and noisy enviorment (SNR=10dB) as shown in Figure 5, NMSE as low as -13.81dB at 19 iterations is achieved by WDO as compared to -8.79dB at 230 iterations, -8.77dB at 19 iterations and -9.76dB at 280 iterations for BFO, GA and LMS respectively. From Figure 7, it is observed that when SNR is increased to 30dB, minimum NMSEobtained by WDO is -27.85dB at 27 iterations as compared to -26.29dB at 200 iterations, -24.24dB at 22 iterations and -27.37dB at 268 iterations for BFO, GA and LMS respectively. Careful observation of Table 3 reveals that convergence rate of GA is better than WDO but NMSE is appreciably large for system identification task. NMSE obtained by LMS at 30dB SNR is almost at par with those obtained by WDO for CH1NL1, CH1NL2, CH2NL1 and CH2NL2 but convergencence is extremly slow in these cases. Thus, WDO performs better thanother methods considered in this work.

The identification performance is tested by feeding a random signal to the plant as well as the adaptive model

Table 4. Estimated plant parameters under different noise conditions and nonlinearities

|              | Channel    | Type of       | WDO       |           | BFO       |           | GA        |           | LMS       |           |
|--------------|------------|---------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
|              | Parameters | non-linearity | SNR: 10dB | SNR: 30dB |
|              | CH1        | NL0           | 0.3002    | 0.3041    | 0.3005    | 0.3187    | 0.3124    | 0.0556    | 0.2749    | 0.3011    |
|              | 0.3040     |               | 0.8656    | 0.8963    | 0.9027    | 0.3366    | 0.8749    | 0.9021    | 0.8753    | 0.9000    |
|              | 0.9029     |               | 0.3174    | 0.2970    | 0.3060    | 0.7593    | 0.3205    | 0.3127    | 0.3385    | 0.3074    |
| _            | 0.3040     |               |           |           |           |           |           |           |           |           |
| Experiment 1 | CH1        | NL1           | 0.1588    | 0.1720    | 0.1880    | 0.2819    | 0.0474    | 0.0308    | 0.2511    | 0.2791    |
| me           | 0.3040     |               | 0.6245    | 0.6406    | 0.8567    | 0.9756    | 0.8436    | 0.8602    | 0.8253    | 0.8524    |
| eri          | 0.9029     |               | 0.1760    | 0.1544    | 0.2491    | 0.2642    | 0.2497    | 0.2497    | 0.3017    | 0.2866    |
| Exp          | 0.3040     |               |           |           |           |           |           |           |           |           |
| ' '          | CH1        | NL2           | 0.2611    | 0.3014    | 0.5513    | 0.9989    | 0.0631    | 0.0456    | 0.2224    | 0.2875    |
|              | 0.3040     |               | 0.8526    | 0.8807    | 0.6472    | 0.8916    | 0.8749    | 0.8826    | 0.6771    | 0.8751    |
|              | 0.9029     |               | 0.3112    | 0.2973    | 0.3069    | 0.3012    | 0.3125    | 0.2970    | 0.1956    | 0.2936    |
|              | 0.3040     |               |           |           |           |           |           |           |           |           |
|              | CH2        | NL0           | 0.2747    | 0.2652    | 0.1325    | 0.6536    | 0.0231    | 0.0113    | 0.2282    | 0.2571    |
|              | 0.2600     |               | 0.9030    | 0.9019    | 0.4211    | 0.9299    | 0.9217    | 0.9384    | 0.8978    | 0.9271    |
|              | 0.9300     |               | 0.2796    | 0.2629    | 0.9008    | 0.5129    | 0.2497    | 0.2498    | 0.2787    | 0.2634    |
| 2            | 0.2600     |               |           |           |           |           |           |           |           |           |
| Experiment 2 | CH2        | NL1           | 0.1182    | 0.1269    | 0.6763    | 0.6879    | 0.2556    | 0.2661    | 0.2113    | 0.2374    |
| me           | 0.2600     |               | 0.6544    | 0.6720    | 0.8835    | 0.3013    | 0.6256    | 0.8769    | 0.8549    | 0.8796    |
| eri          | 0.9300     |               | 0.1222    | 0.1263    | 0.0964    | 0.2425    | 0.2428    | 0.2500    | 0.2765    | 0.2454    |
| Exp          | 0.2600     |               |           |           |           |           |           |           |           |           |
|              | CH2        | NL2           | 0.2450    | 0.2915    | 0.2638    | 0.8428    | 0.2506    | 0.2681    | 0.2182    | 0.2444    |
|              | 0.2600     |               | 0.9179    | 0.8803    | 0.7457    | 0.8781    | 0.9004    | 0.9082    | 0.8800    | 0.9029    |
|              | 0.9300     |               | 0.5168    | 0.3221    | 0.1938    | 0.2580    | 0.2500    | 0.2523    | 0.2690    | 0.2510    |
|              | 0.2600     |               |           |           |           |           |           |           |           |           |

- WDO

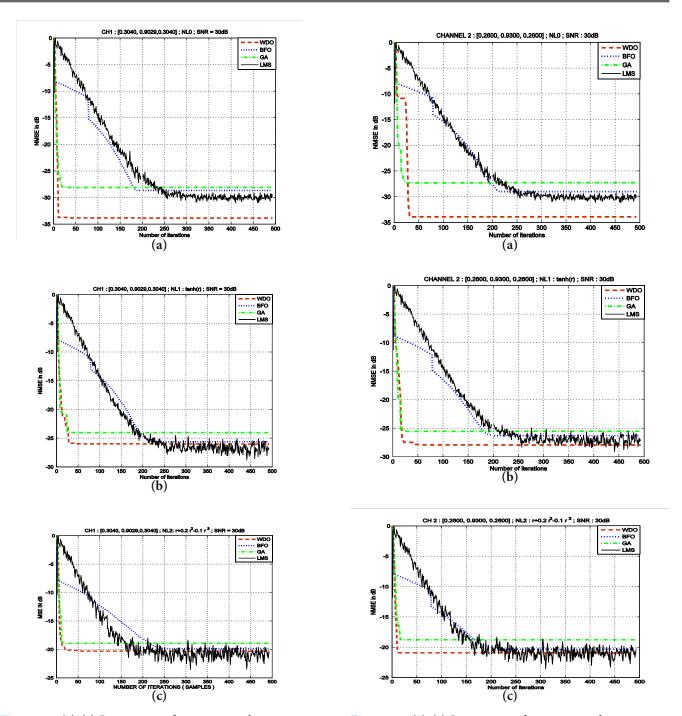


**Figure 4.** (a)-(c) Comparison of convergence characteristics of linear (NL0) and nonlinear (NL1, NL2) channel of experiment-1 at SNR=10dB.

and comparing the desired output with the model output. The results for Experiment 1 at SNR=10dB are demonstrated in Figure 8 and in Figure 9 for SNR=30dB. The results for Experiment 2 at SNR=10dB and 30dB is shown in Figure 10, and Figure 11, respectively. It can be seen that

**Figure 5.** (a)-(c) Comparison of convergence characteristics of linear (NL0) and nonlinear (NL1, NL2) channel of experiment -2 at SNR=10dB.

WDO algorithm perfectly tracks the desired signal for linear channels, CH1NL0 and CH2NL0 at SNR=30dB. The performance degrades when nonlinearity is introduced but it is still better than GA and BFO. However, the performance is at par with LMS method for linear channels

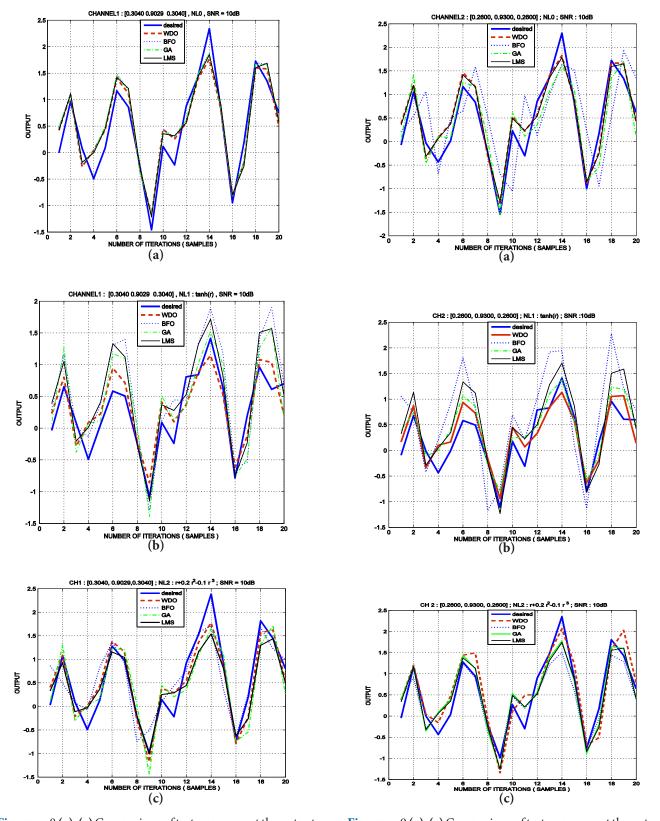


**Figure 6.** (a)-(c) Comparison of convergence characteristics of linear (NL0) and nonlinear (NL1, NL2) channel of experiment- 1 at SNR=30dB.

CH1NL0, CH2NL0 and nonlinear channels CH1NL2, CH2NL2 at 30dB SNR. The tracking capability of WDO is superior to GA and BFO based approaches for both linear and nonlinear channels at 10dB SNR. However, performance of LMS for linear channels CH1NL0 and

**Figure 7.** (a)-(c) Comparison of convergence characteristics of linear (NL0) and nonlinear (NL1, NL2) channel of experiment- 2 at SNR=30dB

CH2NL0 and a class of non-linear channels CH1NL2 and CH2NL2 is similar to WDO in tracking capabilities. Owing to extremely slow convergence rate of LMS, WDO based technique emerges as a suitable candidate for system identification problem.



**Figure.** 8 (a)-(c) Comparison of test responses at the output of the identification model and the plant of experiment-1 at SNR=10dB) using WDO, BFO, GA and LMS algorithms.

**Figure.** 9 (a)-(c) Comparison of test responses at the output of the identification model and the plant of experiment 2 at SNR=10dB using WDO, BFO, GA and LMS algorithms

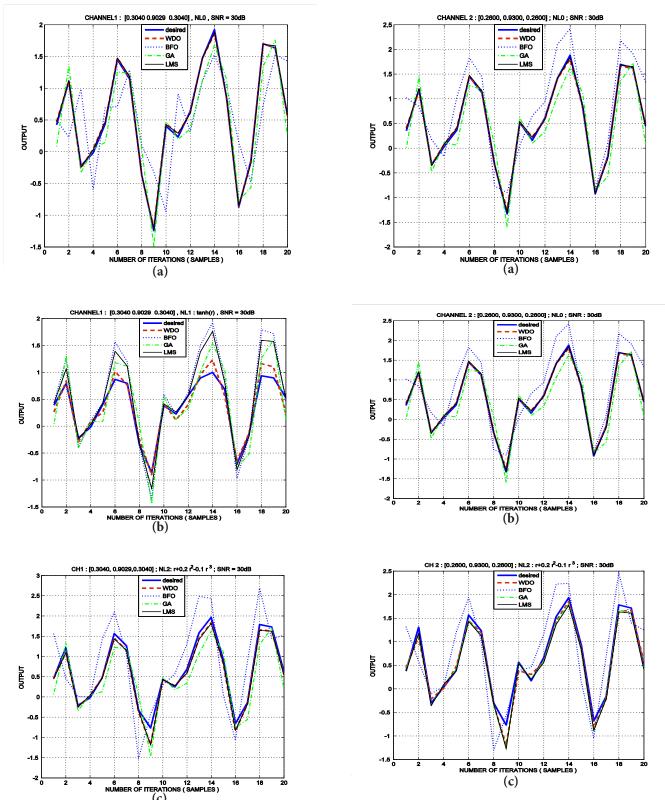


Figure 10. (a)-(c) Comparison of test responses at the output of the identification model and the plant of experiment-1 at SNR=30dB using WDO, BFO, GA and LMS algorithms

Figure 11. (a)-(c) Comparison of test responses at the output of the identification model and the plant of experiment-2 at SNR=30dB using WDO, BFO, GA and LMS algorithms

## 5. Conclusion and Future Scopes

In this work a novel approach to system identification problem is explored by employing WDO technique. Two different FIR filter based communication channels were considered as the unknown plant. Exhaustive simulation results revealed faster and more accurate convergence of plant parameters for various linear and nonlinear systems at SNR 10dB and 30dB. The performance of WDO based method presented in this paper is compared with LMS, GA and BFO based methods. A fairly robust estimate of the plant parameters is obtained by this technique and it is an efficient approach to improve adaptive filter performance in system identification application. The proposed scheme seems interesting and promising as it is able to produce results better than other algorithms under consideration.

The WDO technique can also be tested on dynamic sytems for its tracking capability. It can be clubbed with functional link artificial neural network to improve its accuracy in estimating the plant parameters.

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