Optical Beamforming tuning with Genetic Algorithm and Deep Learning

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Microwave Photonics Systems (MWP) have great potential in latest areas such as 5G networks, Radar, and Internet of things. In order to have low cost, high bandwidth and less complex MWP system, the Optical Beamforming Networks with delay lines, which is integral part of the system, need to have minimum ring resonators with low variation in output and cost. Along with minimum numbers, these Optical Ring Resonators (ORRs) need be tuned to optimize the parameters and minimize the ripples in-group delay. The tuning of Optical Ring Resonators (ORRs) and their Optical Beamforming Network (OBFN) in many ways similar as non-linear optimization problems and can be solved by employing various Machine Learning and Deep Learning Algorithms. In this paper, experimental tuning optimization of Optical Ring Resonators (ORRs) based Optical Beamforming Network (4x1) is proposed by employing Genetic Algorithm & Artificial Neural Networks (ANN) method and optimization results based on group delay responses are compared.
Keywords: Microwave Photonics (MWP) Communication, Beamforming, Optical Ring Resonators (ORR), Genetic Algorithm, Artificial Neural Networks, Deep Learning, Optical Beamforming Networks (OBFN), True Time Delay.

1. Introduction

In wireless communication, Millimeter waves play a very important role due to availability of larger bandwidth and compact devices size. However, traditional RF based systems still have limitation in terms of bandwidth, resolution, speed and functionality. With recent developments in optoelectronics technologies, the new integrated solutions of Microwave Photonics (MWP) can overcome these limitations.

Integrated MWP based Optical Beamforming Networks (OBFNs) systems with new technologies are now more efficient, compact and lightweight. Integrated Optical delay line elements are crucial elements for OBFNs. Optical Ring Resonators (ORRs) are one of the best devices to provide continuous time delay in OBFNs; however, these ORRs need to be tuned to get best results in OBFNs. Various Nonlinear Optimization techniques including Genetic Algorithm are used to get the optimum parameters of ORRs, however for large scale OBFNs, these optimization are not suitable, hence this optimization can be done with the help of Artificial Neural Network (ANN). These standalone optimization approaches however, does not provide the comprehensive overview of the tuning optimization problem and leave best possible optimization adoption to users.

In this paper, experimental tuning optimization of ORR based 4x1 OBFN with Genetic Algorithm and Artificial Neural Network (ANN) techniques is presented. The group delay response of ORR based delay lines is firstly described with mathematically model and subsequently optimized solution is provided with Genetic Algorithm in section III. This section also presented the Artificial Neural Network (ANN) model and application of it in tuning of ORR. Finally, results from both techniques are compared in section IV. Conclusion and future directions are made in section V.

2. MWP System

A Microwave Photonics system consist of both RF and optical components. This combination provides unique opportunity to address the challenges in terms of cost, weight, size and power consumption. MWP offers many advantages in terms of dynamic microwave frequencies with seamless integration with fiber optics network. The broad bandwidth of MWP makes it suitable for realizing broadband optical True Time Delay (TTD). Optical delay lines are integral part of a MWP system to realize the TTD.

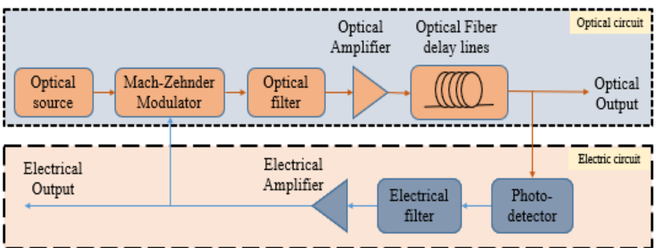

Fig.1.Microwave Photonics System (MZM: Mach-Zehnder Modulator)

A. Optical Beam Forming Network

Optical Beamforming Networks (OBFN) are based on True Time Delay (TTD) which provide low loss in system without limiting bandwidth [1], [2]. This property of OBFN is useful in phase array antenna which solve the problem of Beam squinting. The Major component of OBFNs are Optical delay lines. Fig.2 Shows OBFN based on Multi ORRs delay lines.

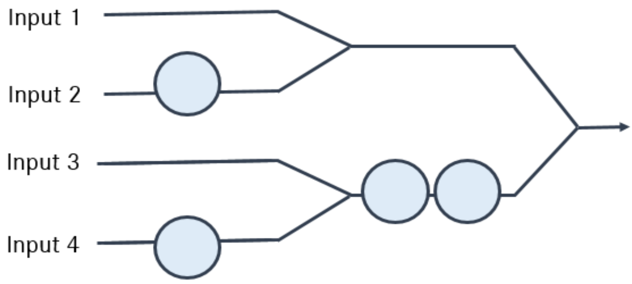

Fig.2. 4x1 ORR based OBFN system

B. Optical Ring Resonators (ORRs)

OBFNs employ multiple ORRs as delay elements in each system of MWP. These ORRs generate desired delays for constructive interferences among signals from different antenna arrays. From construction point of view, an ORR made from straight waveguide and a ring waveguide coupled parallel to it. An ORR behaves an all-pass filter and shows a bell-shaped curve [3] with peak-centered frequency. Group delay spectrum of single ORR can be expressed in below form:

$$\tau'_g(f) = \frac{kT}{2-k-2\sqrt{1-k}\ \mathrm{Cos}\ (\Omega+\emptyset)} \qquad (1)$$

Where k is denoted with Power coupling coefficient, $\emptyset$ as phase offset from the ring resonance. If we use round trip delay of τ to normalize the group delay and frequency, then we can write the expression in below form in normalized FSR range $\Omega = [-\pi, \pi]$ with $\Omega = 2\pi fT$.

$$\tau_g(\Omega) = \frac{k}{2-k-2\sqrt{1-k}\ \mathrm{Cos}\ (\Omega+\emptyset)} \qquad (2)$$

With $\tau_g = {\tau'_g}/{T}$ normalized group delay.

For a specific dimension of ORR, k determines the shape of the curve, whereas phase shift $\emptyset$ determines the resonance frequency of ORR [4]. With increasing k the group delay curve flattens towards x axis. At k equals to 1, the bandwidth becomes infinity and group delay response turned into a flat line.

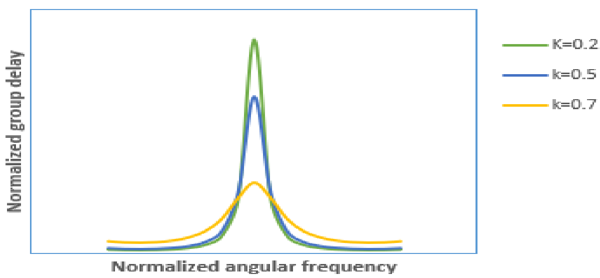

Fig.3. Group delay response of single ORR

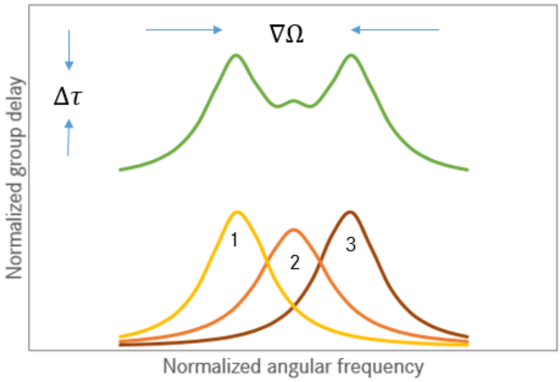

Fig.4. Group delay response of multiple ORRs

The group delay and bandwidth may be limited with single ORR, however, by cascading multiple ORRs, a broadband delay element can be generated and the total group delay response can be expressed by summing the group delay of individual ORRs.

$$\tau_{total}(f) = \sum_l \tau_l\,(f) = \sum_l \frac{k_l T}{2-k_l-2\sqrt{1-k_l}\ \mathrm{Cos}\,(2\pi f T+\emptyset)} \quad (3)$$

Where l is used to differentiate between the ORRs, T is round trip-time.

Cascading multiple ORRs improves the flat delay response with large bandwidth, however there is inherent tradeoff exist between bandwidth, delay, ripple, complexity and number of cascaded rings. Having high number of rings reduces system complexity and improves the bandwidth but at the expense of larger ripple [3],[5].

3. Optimization approach

To get a group delay response with minimum ripple, the setting of k and ∅ should be optimal. The optimum values of these parameters can be arrived from multiple methods. To get the optimize value of group delay, the results can be compared with the ideal flat response with a normalized delay of D. This comparison should be specific bandwidth of interest. This paper presented two main approaches to get the optimum values. i.e. Genetic algorithm and Feed Forward Neural Networks [13],[14].

A. Genetic Algorithm

Genetic algorithm belongs to larger class of evolutionary algorithms. It is Metaheuristic inspired by natural selection and used to get optimum solution by applying biological inspired operators such as Mutation, Crossover and Selection.

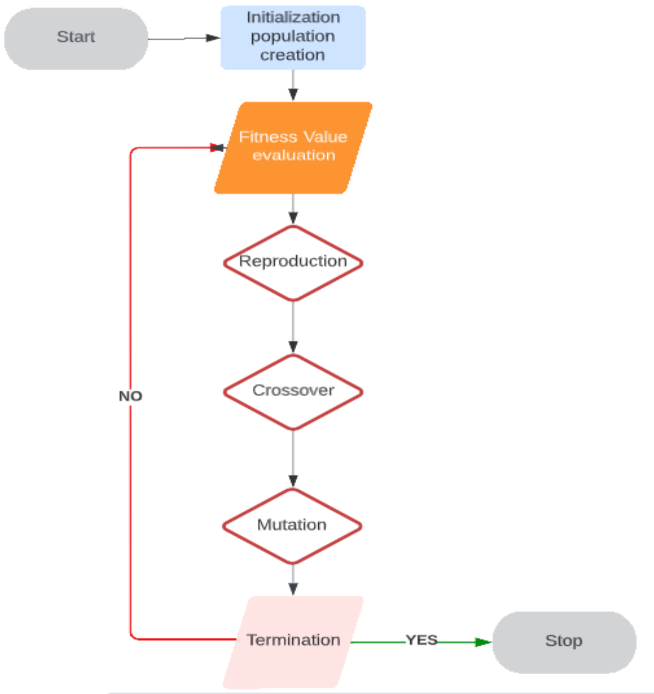

Fig.5. Major implementation steps in Genetic algorithm

Due to evolutionary property of Genetic Algorithm, minimum numbers of generations are required to get global optimum. A random population uniformly covering the whole search space is set up in initial phase. Individual elements of that population is associated with group delay of each ORR with certain frequency ranges and its input-output relation can be evaluated in connection with desired group delay response based on object function that approaches the better solution or fitness for the individuals [6]. In our analysis, the optimization ORR parameters k and $\emptyset$ considered as real values define individual from genetic point of view and are regarded its Chromosomes. In next phase, the subsequent evolution takes place following the rule of natural selection from population based on fitness of individuals. The Algorithms finally terminates when the target fitness is obtained or generation limit is achieved or no further improvement in fitness obtained.

Based on ORR parameters, the fitness function should be function of actual group delay of ORRs involved and desired group delay [7]. The fitness function can also be defined in term of ripple of group delay. In our case, we have used following fitness function

$$f_a = \sum (D - \tau_g)^2 \qquad (4)$$

For implementation of Algorithm, the population of 100 individuals is considered for generation of 1000 numbers. The cross over rate is set at 0.1 and the value of coupling coefficient is limited between .05 and 0.99.

B. Feed Forward Neural Network

The ideal OBFN system need to have minimum ORRs, low cost and with high bandwidth. For designing of this OBFN, the system need to be optimized. Feedforward Neural Network can optimize the results OBFN system by considering it as Non-linear optimization [8]. For this paper, we have considered 4x1 OBFN configuration.

Training examples consist of certain frequencies of signal as input to ORRs and desired delays as output. The signals are assumed to be noise free for simplicity and system is considered as lossless system, i.e., power loss r=1.

- Non-linear Optimization

For a given numbers of training samples, the deep learning algorithm trains the neural network in order to get optimum values of ORR parameters k and $\emptyset$ by minimizing the cost function.

$$C = \sum_{i=1}^{p} (D - A)^2 \qquad (5)$$

Where p is training examples randomly chosen from training sample. D is the desired group delay and A is activation function.

The parameters of ORRs are updated via gradient decent method in following form [9]:

$$\Delta k = \alpha \frac{\partial C}{\partial k}, \quad \Delta \emptyset = \alpha \frac{\partial C}{\partial \emptyset} \qquad (6)$$

Where α is the learning rate. The expression $\frac{\partial C}{\partial k}$ and $\frac{\partial C}{\partial \emptyset}$ can be derived from the following manner

$$\frac{\partial C}{\partial k} = \frac{\partial C}{\partial A}\frac{\partial A}{\partial Z}\frac{\partial Z}{\partial k}, \quad \frac{\partial C}{\partial \emptyset} = \frac{\partial C}{\partial A}\frac{\partial A}{\partial Z}\frac{\partial Z}{\partial \emptyset} \qquad (7)$$

Where Z is the sum of group delay of individual ORRs and Activation function A taken as sigmoid function whose is defined as below

$$A(z) = \frac{1}{1+e^{-z}} \qquad (8)$$

- Backpropagation Algorithm

The non-linear optimization with Gradient Decent need to have the information for the cost function gradient of parameters mentioned [10] in equation no. 6. The best way to have gradient of cost function is to have gradient of all layers of neural network in reverse order [11],[12].

With equation 9, 10 and 11 we can find the gradient for cost function with respect to ORR parameters k and $\emptyset$ which ultimately used to implement the gradient projection method.

$$\frac{\partial C}{\partial A} = 2(D - A) \quad \text{and} \quad \frac{\partial C}{\partial A} = \frac{e^{-z}}{(1+e^{-z})^2} \qquad (9)$$

$$\frac{\partial Z}{\partial k} = \frac{2(\sqrt{1-k}) + (k-2)\text{Cos}\,(\Omega+\emptyset)}{(\sqrt{1-k})\,[2-k-2\sqrt{1-k}\ \text{Cos}\,(\Omega+\emptyset)]} \qquad (10)$$

$$\frac{\partial Z}{\partial \emptyset} = \frac{-\,k\,[2(\sqrt{1-k})\,\text{Sin}\,(\Omega+\emptyset)]}{[2-k-2\sqrt{1-k}\ \text{Cos}\,(\Omega+\emptyset)]^2} \qquad (11)$$

4. Results & Discussion:

The group delay response come from applying multiple ORRs should be optimized as flat as possible in order to overcome the beam squinting problem. For Genetic Algorithm, the fitness function is set with initial parameters and optimization is done based on initial k and $\emptyset$ values with error mentioned in table 1. The coupling coefficient k and phase $\emptyset$ are made constraint and values are kept in the range of zero to1 and $-\pi$ to π respectively. The simulation results in Fig.6 indicates the optimization in group delay based on optimized parameters.

Table1: Initial and optimal parameters of ORR with Genetic algorithm optimization

ORR	Initial k	Initial ø	Initial error
1	0.90000	-1.57080	9.17906181
2	0.90000	-0.78540	
3	0.90000	0.78540	
4	0.90000	1.57080	
ORR	**Final k**	**Final ø**	**Termination error**
1	0.85918	0.72026	0.00176309
2	0.85913	0.72014	
3	0.85920	0.72010	
4	0.85917	0.72026	

With Feed forward Neural Network, the optimization parameters values are indicated in table 2. As numbers of iterations increase, the error function value comes down and brings the optimum value of group delay response, which is finally plotted in Fig.7 for 4x1 and 8x1 configurations.

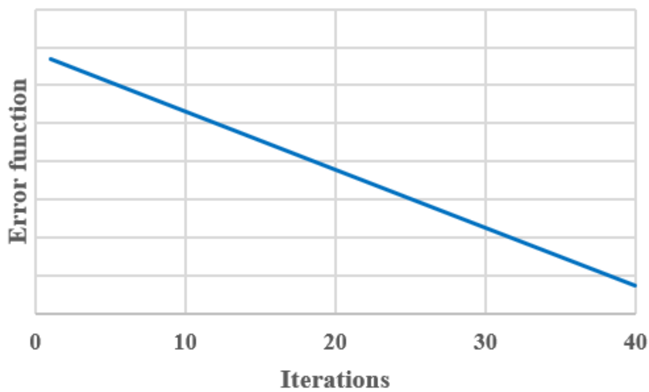

Fig.6. Error function vs iterations diagram for Feed Forward Neural Network

Table 2: Initial and optimal parameters of ORR with Feed Forward Neural Network optimization

ORR	Initial k	Initial ø	Initial error
1	0.90000	-0.6283185	1.16741501
2	0.90000	1.2566371	
3	0.90000	0.0000000	
4	0.90000	1.5707963	
ORR	**Final k**	**Final ø**	**Termination error**
1	0.90568	-0.6248617	0.000115514
2	0.90566	1.3555136	
3	0.90556	0.1763945	
4	0.90525	1.9655253	

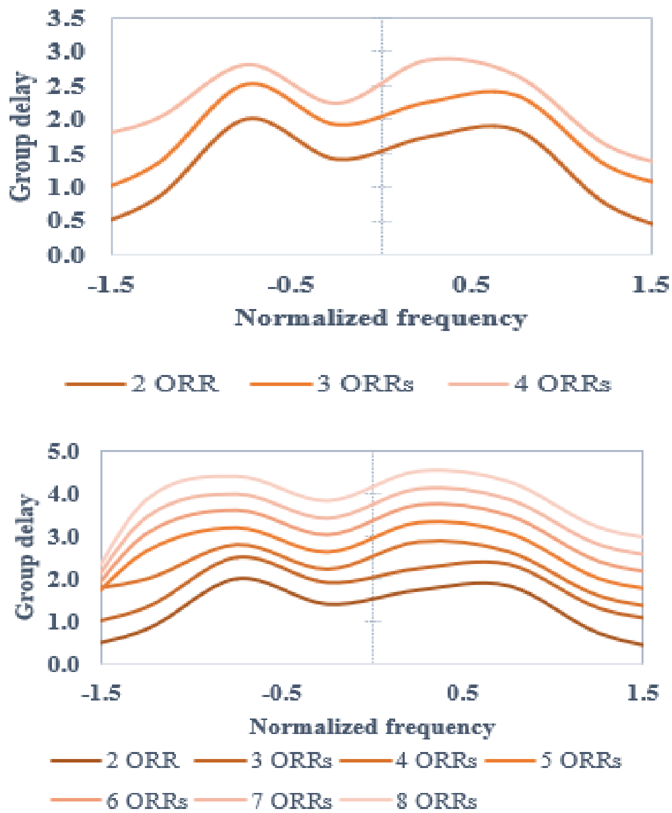

Fig 6. Simulation result of goup delay response of 4x1 and 8x1 OBFN set up with Genetic Algorithm.

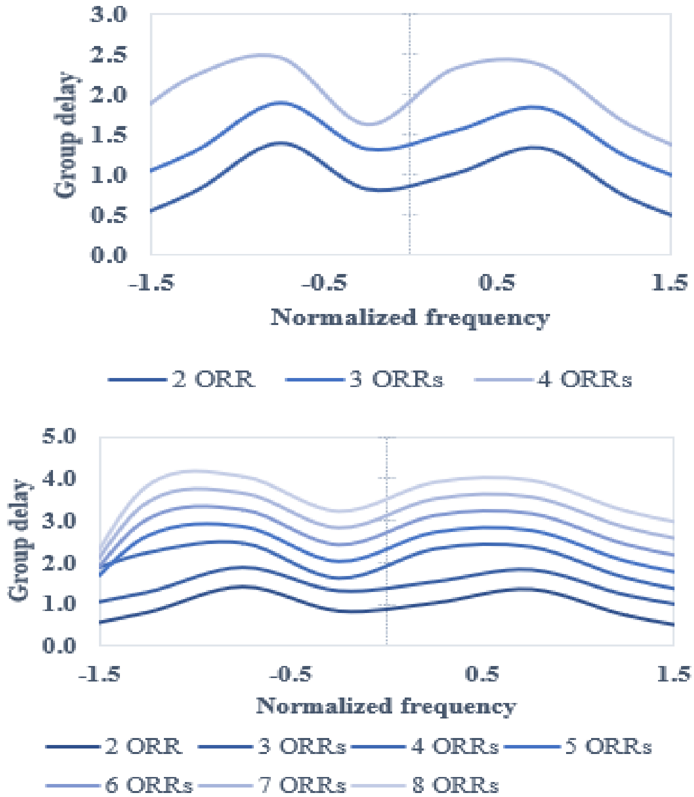

Fig 7. Simulation result of goup delay response of 4x1 and 8x1 OBFN set up with Feed Forward Neural Network

5. Conclusion:

Optical Beamforming Networks (OBFNs) are required to control phased array antennas in wireless communication systems. Tuning OBFNs along with delay elements is highly nonlinear and complex problem. Many algorithms have been deployed to solve and find the tuned parameters in the past. Application of Deep Neural Network is relatively new in this direction. In this work, we reported the 4x1 and 8x1 OBFNs network based ORR delays tuning based on Conventional algorithm, i.e. Genetic Algorithm and relatively new method of Artificial Neural Network. The Group delays ripples shows similarity in both cases, however the approaches for fining the global minimum are different. This work can be further extended to 16x1 and higher configurations with more parameters of ORRs.

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