PSO ALGORITHM USED FOR SEARCHING THE OPTIMUM OF AUTOMATIC PMD COMPENSATION

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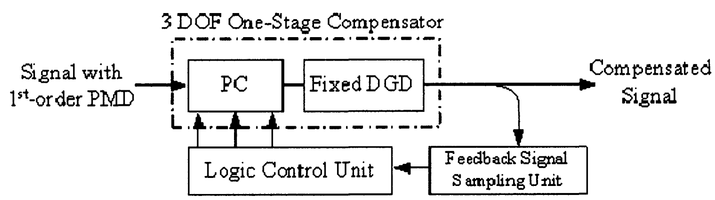
Abstract: The Particle Swarm Optimization (PSO) was introduced into automatic PMD compensation. It showed the merits of rapid convergence to the global optimum not being trapped in local sub-optima in searching process for automatic PMD compensation and robust to noise. In this paper we describe how implementing PSO as a control algorithm in automatic PMD compensation. The comparisons of performances between global version of PSO and local version of PSO were carried out theoretically and experimentally.

1. INTRODUCTION

Adaptive compensation for polarization mode dispersion (PMD) may be one of the urgent tasks for next-generation high bit-rate optical fiber transmission systems. The control algorithm is critical in an adaptive PMD compensator. For adaptive PMD compensation using feedback scheme, many challenges such as rapid convergence to the global optimum without being trapped in local sub-optima, robust to noise etc. make it a hard work to find a practical feedback control algorithm. In most of related literatures, the adopted control algorithms have not been mentioned. Reference [1] and [2] reported the algorithm they used for controlling PMD compensators were gradient based peak search methods. We found that when the numbers of control parameters increased, gradient based algorithm had large numbers of opportunities to be locked into local sub-optima rather than the global-optimum. Besides, it would be less effective for a system with a relatively high noise level in PMD monitor, because the gradient information between neighboring signals would be submerged in noise. For the fist time, we introduced Particle Swarm Optimization (PSO) into adaptive PMD compensation as the control algorithm, which .showed the good performance of rapid convergence to the global optimum without being trapped in local sub-optima and robust to noise.

2. THE ROLE OF CONTROL ALGORITHM IN ADAPTIVE PMD COMPENSATION

The configurations shown in Fig.1 and 2 are the typical schemes of optical post-compensation for PMD. It is widely believed that the one-stage compensators in Fig.1 are able to compensate the PMD to the first-order. They have 3 or 4 parameters (or degree of freedom, DOF) to be controlled depending on whether the differential group delay (DGD) line is fixed or varied. The Two-stage compensators in Fig. 2 can compensate the PMD up to the second-order [3][4]. They have 6 or 7 parameters (or DOF) to be controlled depending on whether the delay line is fixed or varied. (Here, the



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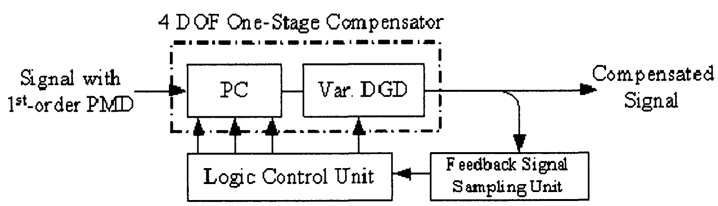
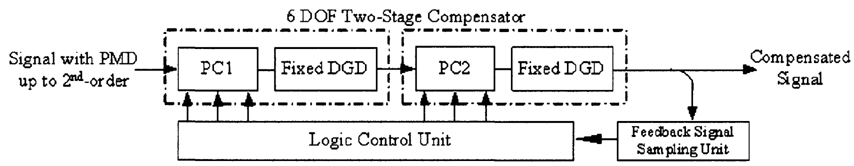


(b)

Figure 1. One-Stage Compensator

reason why we use 3 parameters instead of 2 to adjust polarization controllers (PC) is that, we found in the experiments, only adjusting at least

3 waveplates can a PC transform a fixed input state of polarization (SOP) into output states covering entire Poincaré sphere.)



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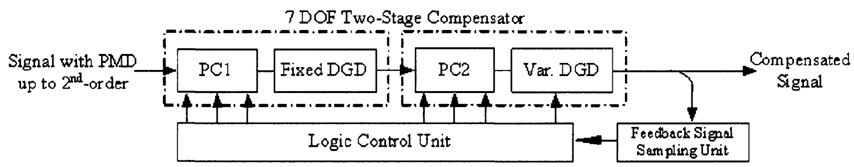

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Figure 2. Two-Stage Compensator

The adaptive PMD compensation is a process for a control algorithm to find optimal combinations of control parameters, in order for the feedback signal to reach a global optimum, in an intelligent, fast, and reliable manner. In our experiment shown in Fig.3, the degree of polarization (DOP), obtained by an in-line polarimeter, was used as feedback signal. The optical pulses at the receiving end have DOP of 1 when there is no PMD in the fiber link, and DOP value decreases as PMD increases. The polarization controller used in compensation unit is the electrically controlled one which has four fiber-squeezer cells to be adjusted with voltage of 0-10V, out of which the three cells were used in the experiment. In this case, the problem of adaptive PMD compensation can be described as the problem of maximization of DOP in mathematics:

$$\underset{parameters}{MAX}\ (function) \tag{1}$$

where the *function* in bracket represents the DOP value in the experiment. The *parameters* here are the voltages for controlling PCs and varied delay line. The *function* in Eq.(1) is not simply predictable in the adaptive PMD compensation system. Therefore a good searching algorithm is required to solve problem (1), which is the problem of searching global maximum in D-dimensional hyperspace. The number of D depends on the number of DOF the compensator scheme chosen as shown in Fig.1 and 2. Generally, the more the DOFs are the more sub-maxima exist, which would increase the hard task of the searching algorithm. Therefore it is more difficult for a searching algorithm to achieve finding the global optimum in the second-order PMD compensation using the two-stage compensator in Fig.2 than in the first-order PMD compensation using the one-stage compensator in Fig.1.

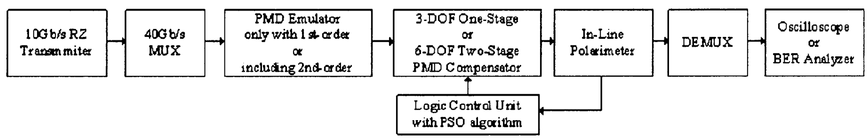


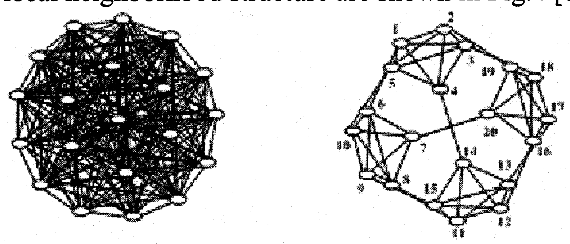
Figure 3. Our experiment setups of one-stage or two-stage adaptive PMD compensation for 40Gb/s OTDM transmission system using PSO algorithm

3. THE PSO OPTIMIZATION TECHNIQUE USED AS THE CONTROL ALGORITHM

The PSO algorithm, proposed by Kennedy and Eberhart [5], has proved to be very effective in solving global optimization for multi-dimensional problems in static, noisy, and continuously changing environments [6]. We introduced for the first time the PSO technique into automatic PMD compensation in our previous works [7] and the latest experiment described in Fig.3, where it was shown to be effective.

The PSO is an optimization technique based on researches on swarms such as bird flocking. According to the research results for bird flocking, birds are finding food by flocking (not by each individual). It leads to the assumption that information is shared in flocking. Therefore it is easier for bird flocking to find only a food in a region than each individual.

At the beginning, the PSO algorithm randomly initializes a population (called swarm) of individuals (called particles). Each particle represents a single intersection of multi-dimensional hyperspace. The position of *i*-th particle is represented by the position vector $X = (x_{i1}, x_{i2}, \cdots, x_{iD})$ .The particles evaluate their position relative to a goal at every iteration. In each iteration every particle adjusts its trajectory (by its velocity $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$) toward its own previous best position, and toward the previous best position attained by any member of its topological neighborhood. Generally, there are two kinds of topological neighborhood structures: global neighborhood structure, corresponding to the global version of PSO (GPSO), and local neighborhood structure, corresponding to the local version of PSO (LPSO). For the global neighborhood structure the whole swarm is considered as the neighborhood, while for the local neighborhood structure some smaller number of adjacent members in sub-swarm is taken as the neighborhood. The two typical topological structures for global and local neighborhood structure are shown in Fig.4 [8].



(a) (b)

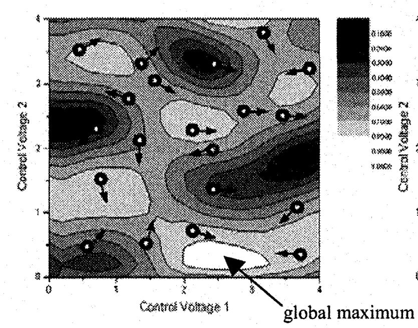
Figure 4. The topologic structure for global neighborhood (a) and one typical topologic structure for local neighborhood (b).

In the global version of PSO, each particle keeps track of its coordinates in hyperspace which are associated with the best solution (fitness) it has achieved so far. (The value of that fitness is also stored.) The value (and its location) is called *pbest*. At the same time, the overall best value, and its location, obtained so far by any particle in the population, is also tracked. This is called *gbest*. The particle swarm optimization concept consists of, at each time step, changing the velocity (accelerating) of each particle toward its *pbest* and *gbest*, at the same time changing its position according to following equations [9]:

$$v_{id} = v_{id} + c_1 \times rand() \times (pbest_{id} - x_{id}) + c_2 \times rand() \times (gbest_d - x_{id}) \quad (2)$$

$$x_{id} = x_{id} + v_{id} \quad (3)$$

where v_{id} is the i-th particle's velocity component, x_{id} is the current position component of the i-th particle, $pbest_{id}$ is the component of *pbest* of i-th particle along d axis, and $gbest_d$ is the component of *gbest* along d axis. The constants c_1 and c_2, termed learning rates, determine the relative influence of *pbest* and *gbest*. The rand() generates pseudo random numbers that are uniformly distributed in the interval of [0, 1]. If any particle's position is close enough to the goal function, it is considered as having found the global optimum and the recurrence is ended. In the global neighborhood structure, each particle's search is influenced by the best position found by any member of the entire population. In contrast, each particle in the local neighborhood structure is influenced only by parts of the adjacent members. In other words, for the local version of PSO (LPSO), particles have information only of their own and their neighbor's bests, rather than that of the entire group. Instead of moving toward the stochastic average of *pbest* and *gbest* (the best location of the entire group), particles move toward points defined by *pbest* and "*lbest*", which is the index of the particle with the best evaluation in the particle's neighborhood. Therefore the local version of PSO has less opportunity to be trapped in sub-optima than the global version of PSO (GPSO). In our experiment 20 particles are used either in GPSO or LPSO.



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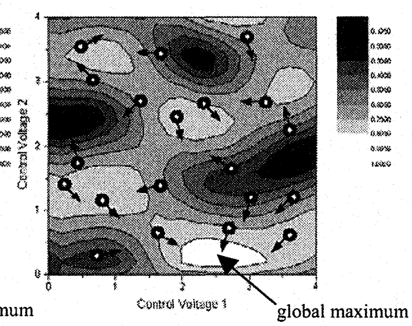

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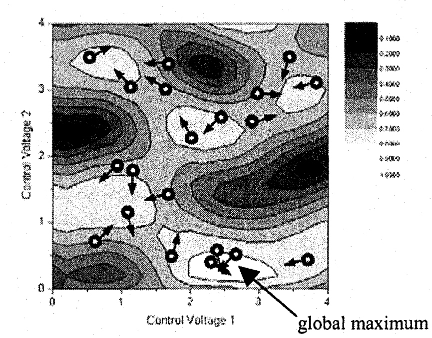
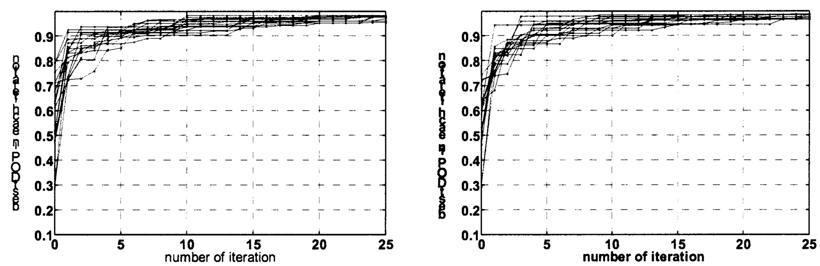


(c)

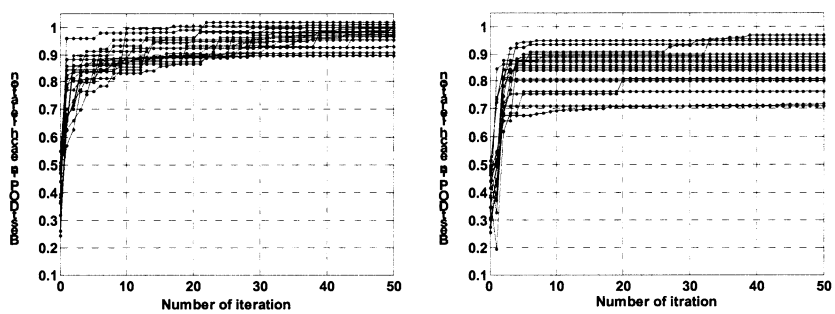
Figure 5. A visualized procedure for demonstrating a process of global maximum searching using PSO algorithm. (a)Initializing a swarm of particles at the beginning; (b)The particles in searching course according to Eq.(2) and Eq.(3); (c)The global DOP maximum has been founded.

Fig.5 is a visualized procedure for demonstrating a process of global maximum searching using PSO algorithm. For the sake of simplicity we choose a searching problem in 2-dimentional space---for example, finding global DOP maximum through controlling two voltages on a PC in the PMD compensator.



(a) (b)

Figure 6. The best DOP vs. iteration recorded in 3-DOF 1st-order PMD compensation using LPSO (a) and GPSO algorithm (b).



(a) (b)

Figure 7. The best DOP vs. iteration recorded in 6-DOF 2nd-order PMD compensation using LPSO (a) and GPSO algorithm (b).

In the adaptive PMD compensation experiment shown in Fig.3, we made the comparison of effectiveness of both GPSO and LPSO, respectively either used in 3 DOF one-stage or in 6-DOF two-stage PMD compensation. At first, we made 18 times of the 1^{st}-order PMD compensation experiments with the one-stage compensator by controlling the three voltages of the electrically controlled PC in the compensator through GPSO and LPSO algorithm, respectively. We made randomly the 18 kinds of different initial PMD states of the PMD emulator (corresponding to 18 different initial DOP values) for 18 times of experiments. In every process of global DOP maximum searching, we recorded variation of best DOP values in each iteration, and the maximum iteration number is set to 25, with the results shown in Fig.6. It can be seen that all the final searched DOP values in any compensation process exceed 0.95 whatever the GPSO or LPSO is used as control algorithm. And all the DOP values reach 0.9 within about 8 iterations for both GPSO and LPSO. The reasons why there is nearly no difference between the cases using LPSO and GPSO are less local sub-optima existed and low level of noise for the sake of relatively simple configuration of 3-DOF one-stage compensation system. Therefore it is not so difficult for both GPSO and LPSO to undertake.

Secondly, in comparison, we also made 18 times of the 2^{nd}-order PMD compensation with the two-stage compensator by controlling six voltages of two PCs in the compensator also through GPSO and LPSO algorithm, respectively. Differently, the maximum iteration number for each searching process is set to 50, since we guess that it is more difficult searching task because of more complicate configuration or more DOF, and higher level of noise.

The results are shown in Fig.7(a) and (b). It is easy to obtain a conclusion that, because of more local sub-maxima and higher noise level in 6-DOF system than in 3-DOF system, for the case of using GPSO there are some initial PMD states that only makes DOP reach the value of 0.7 (Fig.8(b)), corresponding to being trapped in local sub-optima. In contrast, for the case of using LPSO all final searched DOP values exceed 0.9 no matter what initial PMD state is. And all the DOP values reach 0.9 within about 25 iterations. We can draw a conclusion that LPSO have more powerful ability to undertake the task for solving multi-dimensional problem, and then is a better searching algorithm for adaptive PMD compensation up to high-order.

The response time of the compensator depends on the strategy of the chosen algorithms and the performance of the hardware including A/D, D/A, voltage-controlled polarization controller, etc. We can define a time unit as the time used for one particle treatment in a PMD compensation loop. Many events happen in one time unit: (1) D/A converters writing multi-voltages to the voltage-controlled PCs, (2) waiting for the PCs to reach their steady states, (3) multiple A/D conversions, (4) processing the data in the computer processor with the PSO algorithm. Then the next D/A conversion begins. In our experiment one time unit was measured to be about 0.8ms for 3-DOF and 1.1ms for 6-DOF system. One iteration (containing 20 particles treatment) for searching is equivalent to 20 time units. If we set DOP value of 0.9 as the criterion which is considered to achieve the goal to complete the compensation, the compensation time used is:

$$\text{compensation time} = \text{time unit} \times \text{number of particles} \\ \times \text{iterations used to reach the criterion} \tag{4}$$

So for 1st-order compensation by 3-DOF one-stage compensator the compensation time is 0.8×20×8=128ms. And for 2nd-order compensation by 6 DOF two-stage compensator using LPSO algorithm the compensation time is 1.1×20×25=550ms. By analyzing time used by every part of hard wares and algorithm, we find the PSO algorithm only occupies fewer than 16% of the whole time. Therefore if we can afford to high speed hardwares the compensator with faster speed of real level of milliseconds can be achieved.

Furthermore, the PSO algorithm can also be used as the control algorithm for multi-channel PMD compensation like in WDM system. One of feasible strategy is trying to keep the worst compensated channel as good as possible, which can be described as another maximization problem as follows:

$$\underset{parameters}{MAX}\left(\underset{j}{MIN}\left(function_j\right)\right) \tag{5}$$

where j represents the j-th channel and the other parameters are similar to those in single channel.

4. CONCLUSION

In conclusion, for the first time we have introduced PSO algorithm into adaptive PMD compensation, which showed the good performance of rapid convergence to the global optimum without being trapped in local sub-optima and robust to noise. With comparison of using GPSO and LPSO in the one-stage and the two-stage adaptive PMD compensation in 40Gb/s OTDM transmission system, the LPSO algorithm is proved to be more suitable for solving with multi-DOF PMD compensation. With PSO algorithm, we have achieved the automatic PMD compensation with several hundreds of milliseconds. And it is shown that the compensator with PSO algorithm has deep potential to increase its response speed. We also made an expectation to use PSO for PMD compensation in WDM system.

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REFERENCES

[1] R. Noé, D. Sandel, M. Yoshida-Dierolf, S. Hinz, V. Mirvoda, A. Schöpflin, C. Glingener, E. Gottwald, C. Scheerer, G. Fischer, T. Weyrauch, and W. Haase, "Polarization mode dispersion compensation at 10, 20, and 40Gb/s with various optical equaliziers," J. Lightwave Technol., Vol. 17, pp1602-1616, 1999.

[2] J. C. Rasmussen, "Automatic PMD and chromatic dispersion compensation in high capacity transmission," 2003 Digest of the LEOS Summer Topical Meetings, pp47-48, 2003.

[3] J. Patscher and R. Eckhardt, "Component for second-order compensation of polarization-mode dispersion," Electron. Lett., Vol. 33, No.13, pp1157-1159, 1997.

[4] S. Kim, "Schemes for complete compensation for polarization mode dispersion up to second order," Opt. Lett. Vol 27, No 8, pp577-579, 2002.

[5] J. Kennedy and R. C. Eberhart, "Paticle Swarm Optimization," Proc. of IEEE International Conference on Neural Networks, Piscataway, NJ, USA, pp1942-1948, 1995.

[6] E. C. Laskari, K. E. Parsopoulos, and M. N. Vrahatis, "Particle Swarm Optimization for Minimax Problems," Proc. of the 2002 Congress on Evolutionary Computition, Vol.2, pp1576-1581, 2002.

[7] Xiaoguang Zhang, Li Yu, Yuan Zheng, Yu Shen, Guangtao Zhou, Bojun Yang, "Adaptive PMD compensation using PSO algorithm," OFC'2004, Los Angeles, CA, 2004, Paper ThF1.

[8] J. Kennedy and R. Mendes, "Population Structure and Particle Swarm Performance," Proc. of the 2002 Congress on Evolutionary Computition, Vol.2, pp1671-1676, 2002.

[9] R. Eberhart and J. Kennedy, "A New Optimizer Using Particle Swarm Theory," Proc. of the Sixth International Symposium on Micro Machine and Human Science, pp39-43, 1995.