Inertia Weight Strategies in GbLN-PSO for Optimum Solution

Nurul Izzatie Husna Fauzi
Faculty of Computing,
Universiti Malaysia Pahang Al-Sultan Abdullah,
26600 Pekan, Pahang, Malaysia
izzatiehusna@ump.edu.my

Zalili Musa *
Faculty of Computing,
Universiti Malaysia Pahang Al-Sultan Abdullah,
26600 Pekan, Pahang, Malaysia
zalili@ump.edu.my

2023 IEEE 8th International Conference On Software Engineering and Computer Systems (ICSECS) | 979-8-3503-1093-1/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICSECS58457.2023.10256385

Abstract—**Particle Swarm Optimization (PSO) is the popular metaheuristic search algorithm that is inspired by the social learning of birds and fish. In the PSO algorithm, inertia weight is an important parameter to determine the searching ability of each particle. When the selected inertia weight is not suitable, the searching particles are more focused on one direction or area nearest to the local best. Therefore, the movement of the particles is limited and not spreading during the search process. Thus, this will cause the particles fast to converge. As the result, the particle is trapped in local optimal. To overcome this problem, we used three different inertia weight strategies such as Constant Inertia Weight (CIW), Random Inertia Weight (RIW), and Linear Decreasing Inertia Weight (LDIW) to analyze the impact of inertia weight on the performance of Conventional PSO and the enhancement of PSO called Global Best Local Neighborhood-PSO (GbLN-PSO) algorithm. In order to test the performance of the three different inertia weight strategies, we test these algorithms in different sizes of search space with random values. Based on the comparison result of 30 simulations, it shows that GbLN-PSO using RIW was producing a better search result compared to CIW and LDIW. Furthermore, the result shows an improvement in GbLN-PSO searching ability.**

Keywords — PSO, GbLN-PSO, Constant Weight, Random Weight, Linear Decreasing Weight

I. INTRODUCTION

Particle Swarm Optimization (PSO) algorithm was introduced by Eberhart and Kennedy in 1995 [2]. This algorithm was inspired from the social learning of bird and fish [1]. PSO has been used in many real-case applications such as object tracking [3]–[5], task scheduling [6]–[8] and traveling salesman[9], [10].

At the beginning of PSO studies, the inertia weight was not included as one of the parameters [11]. This limitation prevents the particle from being able to control the impact of the previous history of velocities on the current one. Thus, this problem will affect the exploration and exploitation of the particles.

In1998, Shi and Eberhart introduced a significant parameter known as inertia weight [12]. This parameter plays a crucial role in influencing the velocity of a particle [13]–[17]. Moreover, the inertia weight determines the contribution rate of a particle's previous velocity to current velocity. This contribution is important to control and balance the particles global search ability and local search ability [18]–[20].

Inertia weight is an important parameter but selecting the wrong value for it can significantly affect the searching ability, convergence rate, and exploration and exploitation of the particle [21], [22]. Due to this limitation, many researchers have proposed various strategies of inertia weight in order to improve the searching capability of PSO algorithm. These strategies aim to overcome the limitations causes by improper inertial weight selection and enhance the searching efficiency toward the optimal solution.

Since a large number of variations in inertia weight have been test in PSO. Thus, this paper proposes to analyze the performance result of three different inertia weight strategies in Global Best Local Neighborhood in Particle Swarm Optimization (GbLN-PSO) algorithm. Hence, the contribution of this paper is: 1) To compare the performance of three different Inertia Weight strategies in GbLN-PSO algorithm, 2) To evaluate the performance of the comparison Inertia Weight in term of optimum value, mean error, minimum mean error and success rate.

The rest of the paper is structured as follows. Section 2 presents the related word. Section 3 describes the experimental setup used in this paper. Meanwhile, section 4 reveals the experimental results for the inertia weight strategies. Finally, the conclusions a presented in Section 5.

II. RELATED WORK

Inertia Weight plays a crucial role in achieving a balance between exploration and exploitation in the PSO algorithm. In order to enhance the efficiency of PSO, several state-of the-art methods have been developed specifically for improving the handling of the inertia weight [23], [24].

For instance, Shi and Eberhart introduced the Constant Inertia Weight (CIW) in PSO to optimize the search for the optimum solution [12]. The authors suggested a range of [0-1.4] for selecting the inertia weight. In their experiments, they compare the performance of PSO using the inertia weight within range of [0.5-0.8]. The finding shows that by selecting the appropriate inertia weight will enhance the global search ability of the algorithm. However, CIW may lead to suboptimal convergence rate and certain constant value is suitable to certain optimization problem.

Furthermore, Eberhart and Shi proposed a Random Inertia Weight (RIW), which has been shown to enhance the convergence of PSO in early iterations [25]. The results show that RIW strategy aids in achieving the global optimum and addresses the issues of getting trapped in local optima. However, despite its advantages, RIW still has difficulty in determining an optimal range which can affect the exploration and exploitation balance.

Therefore, Linear Decreasing Inertia Weight (LDIW) was introduced to enhance the performance of searching