

## APPENDIX: LOCAL CONVERGENCE PROOF OF THE PSO METHOD

The update function of the moving velocity of the ellipse parameters can be expressed as:

$$\mathbf{v}_k^{t+1} = \omega \mathbf{v}_k^t + c_1 r_1 (\mathbf{x}_{k,pb} - \mathbf{x}_k^t) + c_2 r_2 (\mathbf{x}_{gb}^i - \mathbf{x}_k^t) \quad (1)$$

where,  $\mathbf{x}_k^t = \{E_1^t, \dots, E_s^t; R_0^t\}$  represents the ellipse parameters at time  $t$ ,  $\mathbf{x}_{k,pb} = \{E_1^k, \dots, E_s^k; R_0^k\}$  represents the optimized ellipse parameters of the  $k$ th particle,  $\mathbf{x}_{gb}^i = \{E_1^*, \dots, E_s^*; R_0^i\}$  represents the optimized ellipse parameters among all particles for the  $i$ th circular target,  $\mathbf{v}_k^t$  represents the moving velocity of the ellipse parameters of the  $k$ th particle at time  $t$ ,  $\omega$  represents the inertia weight of the moving velocity of the ellipse parameters,  $c_1$  and  $c_2$  represent cognitive coefficient of  $\mathbf{x}_{k,pb}$  and social coefficient of  $\mathbf{x}_{gb}^i$ , respectively, and  $r_1, r_2 = \text{rand}()$ .

The update function of the optimized ellipse parameters can be expressed as:

$$\mathbf{x}_k^{t+1} = \mathbf{x}_k^t + \mathbf{v}_k^{t+1} \quad (2)$$

Combined (1) with (2), the following formulation can be introduced by:

$$\begin{aligned} \mathbf{x}_k^{t+1} = & [1 + \omega - (c_1 r_1 + c_2 r_2)] \mathbf{x}_k^t - \omega \mathbf{x}_k^{t-1} \\ & + c_1 r_1 \mathbf{x}_{k,pb} + c_2 r_2 \mathbf{x}_{gb}^i \end{aligned} \quad (3)$$

The expectation of (3) can be further simplified as:

$$\begin{aligned} E(\mathbf{x}_k^{t+1}) = & \left(1 + \omega - \frac{c_1 + c_2}{2}\right) E(\mathbf{x}_k^t) \\ & - \omega E(\mathbf{x}_k^{t-1}) + \frac{c_1 \mathbf{x}_{k,pb} + c_2 \mathbf{x}_{gb}^i}{2} \end{aligned} \quad (4)$$

The characteristic equation of (4) can be expressed as:

$$\lambda^2 - \left(1 + \omega - \frac{c_1 + c_2}{2}\right) \lambda + \omega = 0 \quad (5)$$

Assume that two solutions of (5) are  $\lambda_1$  and  $\lambda_2$ . If  $|\lambda_1|$  and  $|\lambda_2|$  are both less than 1, then  $E(\mathbf{x}_k^t)$  is convergent. And it is proved that the necessary and sufficient condition is  $0 \leq \omega < 1$  and  $0 < c_1 + c_2 < 4(1 + \omega)$ , while

$E(\mathbf{x}_k^t)$  is convergent to  $\frac{c_1 \mathbf{x}_{k,pb} + c_2 \mathbf{x}_{gb}^i}{c_1 + c_2}$ .

The variance of (3) can be expressed as:

$$\begin{aligned} D(\mathbf{x}_k^{t+2}) = & (\psi^2 + R^t - \omega) D(\mathbf{x}_k^{t+1}) - \omega (\psi^2 + R^t - \omega) D(\mathbf{x}_k^t) \\ & + R \left[ (E(\mathbf{x}_k^{t+1}) - \mu)^2 + \omega (E(\mathbf{x}_k^t) - \mu)^2 \right] \\ & - 2T \left[ E(\mathbf{x}_k^{t+1}) - \mu + \omega (E(\mathbf{x}_k^t) - \mu) \right] \\ & + \omega^3 D(\mathbf{x}_k^{t-1}) + Q(1 + \omega) \end{aligned} \quad (6)$$

$$\text{where, } \nu = \frac{c_1 + c_2}{2}, \quad \mu = \frac{c_1 \mathbf{x}_{k,pb} + c_2 \mathbf{x}_{gb}^i}{c_1 + c_2}, \quad \psi = 1 + \omega - \nu,$$

$$R^t = c_1 r_1 + c_2 r_2 - \nu, \text{ and } Q^t = \frac{c_1 c_2 (r_1 - r_2) (\mathbf{x}_{gb}^i - \mathbf{x}_{k,pb})}{c_1 + c_2}.$$

The characteristic equation of (6) can be expressed as:

$$\lambda^3 - (\psi^2 + R^t - \omega) \lambda^2 + \omega (\psi^2 - R^t - \omega) \lambda - \omega^3 = 0 \quad (7)$$

Similarly, it is proved that the convergent condition is  $0 \leq \omega < 1$ ,  $c_1 + c_2 > 0$ , and  $f(1) > 0$ , while  $D(\mathbf{x}_k^t)$  is convergent to  $\frac{1}{6f(1)} \left( \frac{c_1 c_2}{c_1 + c_2} \right)^2 (\mathbf{x}_{gb}^i - \mathbf{x}_{k,pb})^2 (1 + \omega)$ ,

among them,  $f(1) = -(c_1 + c_2) \omega^2 + c_1 + c_2 - \frac{1}{3} c_1^2 - \frac{1}{3} c_2^2 + \left( \frac{1}{6} c_1^2 + \frac{1}{6} c_2^2 + \frac{1}{2} c_1 c_2 \right) \omega - \frac{1}{2} c_1 c_2$ .

All in all, if and only if  $0 \leq \omega < 1$ ,  $c_1 + c_2 > 0$ , and  $0 < f(1) < \frac{c_2^2 (1 + \omega)}{6}$ , the PSO method is convergent to  $\mathbf{x}_{gb}^i$  with probability 1.