Artificial plant optimisation algorithm with three-period photosynthesis

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Abstract: In the standard version of artificial plant optimisation algorithm (APOA), the light responsive curve of photosynthesis operator is selected as rectangular hyperbolic model. However, different light responsive curve may result in different performance, therefore, a combination of some different light responsive curves may increase the effectiveness of photosynthesis operator. In this paper, the whole evaluation process is divided into three parts, while different light responsive curve is selected in each part. With orthogonal experimental design, an optimal combination model is determined which consists of parabola model, updated rectangular hyperbolic model and straight line model, and is called three-period photosynthesis operator. To test the performance, some famous benchmarks are employed to test, and simulation results show it is effective.

Keywords: artificial plant optimisation algorithm; APOA; parabola model; updated rectangular hyperbolic model; straight line model.

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1 Introduction

Bio-inspired computation is a subset of natural computation that models the living phenomana, generally, it consists many counterparts, such as genetic algorithm, particle swarm optimisation (PSO) (Cui et al., 2012a, 2012b), ant colony optimisation (ACO) (Xiao et al., 2012a, 2012b), group search optimiser (He et al., 2009), artificial physics optimisation (Xie et al., 2012), biogeography-based optimisation (Lohokare et al., 2011) and seeker optimisation algorithm (Dai et al., 2010).

Artificial plant optimisation algorithm (APOA) is one new evolutionary methodology recently proposed by Cui et al. (2012c, 2012d). APOA simulates the plant growing process, each individual is called one potential branch, and grows according to photosynthesis, phototropism and apical dominance mechanisms. Photosynthesis operator is dedicated to producing the energy created by sunlight and other materials while phototropism operator guides the growing direction according to different conditions. In addition, apical dominance operator is essential to make minor adjustment for the growing directions.

Photosynthesis operator measures the growing energy obtained by each branch, therefore, it is important for the performance. In the standard version, the light responsive curve of photosynthesis operator is selected as rectangular hyperbolic model, however, according to Cai et al.'s (2012) work, other models may provide different performance especially for parabola model. Therefore, in this paper, we focus on the combination selection problem of light responsive curves, and propose a new photosynthesis operator.

The rest of this paper was organised as follows: Section 2 provides a short introduction for the standard version of artificial plant optimisation algorithm, as well as in Section 3, our new photosynthesis operator is illustrated, finally, the simulation results are provided.

2 Standard version of APOA

2.1 Main method

To simulate the plant growing phenomenon, it is important to provide a connection between growing process and optimisation problem. In principle, the search space should be mapping into the whole plant growing environment, and each individual denotes a virtual branch. Moreover, the provisions should be supplied. For example, water, carbon dioxide and other materials are supposed to be inexhaustible except the sunlight. Since the light intensity is varying for different branches, it could be considered as the fitness value for each branch. More details can be found in Table 1.

Table 1 Similarity between plant growing process and optimisation problem

Problem search space	*Plant growing environment*
Iteration	Growing period
Global optimum	Highest light intensity
Fitness value	Light intensity
Point	Branch
Position update	Branch growth

Furthermore, the pseudo code of the standard artificial plant optimisation algorithm is listed in Algorithm 1.

The procedure $Initialisation$ is used to sample m branches randomly from the problem search space, which is an n-dimensional hyper-cube. Each coordinate of a point is assumed to be uniformly distributed between the corresponding upper and lower bounds. The procedure $Calc()$ means the computation of the fitness values for all branches.

Algorithm 1

```
Initialisation ()
Iteration ← 1
while iteration < MAXITER do
Calc ()
Photosynthesis ()
Phototropism ()
Apical dominance ()
Iteration ← iteration + 1
end while
```

2.2 Photosynthesis operator

Photosynthesis is aiming at producing the energy for the branch growing. In Wikipedia, photosynthesis is defined as follows (http://en.wikipedia.org/wiki/Photosynthesis):

> "Photosynthesis occurs in plants, algae, and many species of bacteria, but not in archaea. Photosynthetic organisms are called photoautotrophs, since they can create their own food. In plants, algae, and cyanobacteria, photosynthesis uses carbon dioxide and water, releasing oxygen as a waste product. Photosynthesis is vital for all aerobic life on Earth."

Photosynthetic rate plays an important role to measure how much energy produced. In botany, light response curve is used to measure the photosynthetic rate, and many models have been proposed in the past research, such as rectangular hyperbolic model, non-rectangular hyperbolic model, updated rectangular hyperbolic model, parabola model, straight line model and exponential curve models (Ye and Yu, 2007). In the standard version, rectangular hyperbolic model is employed to measure the quality of the obtained energy:

$$p_i(t) = \frac{a \cdot Uf_i(t) \cdot P_{max}}{a \cdot Uf_i(t) + P_{max}} - R_d$$

where $p_i(t)$ is the photosynthetic rate of branch i at time t, a is the initial quantum efficiency, P_{max} is the maximum net photosynthesis rate and R_d is the dark respiratory rate, $Uf_i(t)$ denotes the light intensity and is defined as follows:

$$Uf_i(t) = \frac{f_{worst}(t) - f_i(t)}{f_{worst}(t) - f_{best}(t)} \tag{1}$$

where $f_{worst}(t)$ and $f_{best}(t)$ are the worst and best light intensity at time t, respectively, as well as $f_i(t)$ means the light intensity of branch i.

The steps of photosynthesis operator are listed in Algorithm 2.

Algorithm 2 Photosynthesis ()

```
for i = 1 to m do
Computing the light intensity Uf_i(t)
Computing the photosynthetic rate p_i(t)
end do
```

2.3 Phototropism operator

In Wikipedia, phototropism is defined as follows (http://en.wikipedia.org/wiki/Phototropism):

> "Phototropism is directional growth in which the direction of growth is determined by the direction of the light source. In other words, it is the growth and response to a light stimulus. Phototropism is most often observed in plants, but can also occur in other organisms such as fungi."

In phototropism operator of APPM (Cui et al., 2012c), the gravity is omitted, and all branches are updated with the same manner. However, the growing direction of each branch should be changed dynamically due to the gravity. To account for this phenomenon, the phototropism operator is re-designed in the standard version by employing the influence of gravity to adjust the growing direction. In nature, the gravity plays a significant role on the growing direction if the branch is long enough. Therefore, in the standard version, the population is divided into two species: growing-motion branch and maturing-motion branch.

If branch i belongs to the growing-motion branch, it grows as follows:

$$x_i^k(t+1) = x_i^k(t) + (p_i^k(t) - x_i^k(t)) \cdot growth \cdot r \tag{2}$$

where $growth$ is one parameter, r is one random number sampled with uniform distribution, and

$$\overrightarrow{p_i} = \arg\min\{f(\overrightarrow{x_i}(gen))|gen = 1, 2, ..., t\}$$

On the contrary, if branch i is located in the maturing-motion branch, the growing motion is defined by:

$$x_i^k(t+1) = x_i^k(t) + growth \cdot r \cdot D_i^k(t) \tag{3}$$

where $D_i^k(t) = (d_i^1, d_i^2, \cdots, d_i^n)$ is the bending degree that translates Cartesian coordinate into polar coordinate as follows:

$$d_i^1 = \prod_{p=1}^{n-1} cos(angle_i^p)$$

$$d_i^1 = sin(angle_i^k) \prod_{p=1}^{n-1} cos(angle_i^p)$$

$$d_i^n = sin(angle_i^{n-1})$$

At each iteration, one branch maintains one parameter $\overrightarrow{angle_i} = (angle_i^1, angle_i^2, ..., angle_i^n)$ (n denotes the dimensionality) to reflect the gravity influence, and is updated with:

$$angle_i^k(t+1) = angle_i^k(t) + \theta_i^k \tag{4}$$

where

$$\theta_i^k = K_{oi}^k \sqrt{|\cos(\theta + angle_i^k) - \cos(\omega + angle_i^k)|}$$

The θ is a constant between interval $[\frac{\pi}{40}, \frac{\pi}{2}]$, and ω is in $[\frac{\pi}{20}, \frac{\pi}{2}]$, K_{oi}^k is calculated by,

$$K_{oi}^k = 2\sqrt{\frac{|p_i^k|}{0.25\pi R_e}}$$

where R_e is a constant between 0 and 2.

The pseudo code is listed as in Algorithm 3.

Algorithm 3 Photosynthesis ()

```
for i = 1 to m do
Sorting the fitness values of all branches,
  the better half of the best populations are taken as
  growing-motion branches, as well as other branches
  are maturing-motion branches
Updating the position for growing-motion branch
Updating the position for maturing-motion branch
end do
```

2.4 Apical dominance operator

Apical dominance is also an important phenomenon. In Wikipedia, apical dominance is defined by (http://en.wikipedia.org/wiki/Apical_dominance):

> "Apical dominance is the phenomenon whereby the main central stem of the plant is dominant over (i.e., grows more strongly than) other side stems; on a branch the main stem of the branch is further dominant over its own side branchlets."

In apical dominance phenomenon, all buds are divided into two parts: apical bud and lateral bud. For each branch, the growing buds may affect the branch growing direction significantly. Therefore, if we want to change the growing direction for some branches, we may make manual pruning process to remove the apical bud, this may enhance the exploration capability to escape from local optimum. On the country, if we still let apical bud to survive, then the exploitation may focus on the neighbours of this bud.

In APOA, the best position of all branches can be viewed as the apical bud because its fitness value (light intensity) is better than other buds. Furthermore, if there are at least two branches with the same light intensities, only one branch would be selected with uniformly distribution eventually.

Suppose $\overrightarrow{g}(t)$ is the best position in the current population, in other words, it is satisfied with

$$\overrightarrow{g}(t) = \arg\min\{f(\overrightarrow{p_i}(t))|i = 1, 2, ..., n\} \tag{5}$$

apical dominance operator is then performed on $\overrightarrow{g}(t)$ because it achieves the best performance. Suppose $rand(1)$ and $rand(2)$ are two random numbers with uniformly distribution, then one of the following manners will be performed according to difference conditions ($rate$ is a parameter):

If $rand(1) < rate$

$$g^k(t+1) = (g^k(t) - x^k_{worst}(t)) \cdot growth \cdot r \tag{6}$$

Else if $rand(2) < 1/n$

$$g^k(t+1) = x_{max} + (x_{max} - x_{min}) \cdot r \tag{7}$$

Else

$$g^k(t+1) = g^k(t) \tag{8}$$

The pseudo code is listed as in Algorithm 4.

Algorithm 4 Apical dominance ()

```
1: Determining the position g(t)
2: Selecting two random numbers rand(1) and rand(2)
3: Updating the position g(t)
   according to the value of rand(1) and rand(2)
```

3 Three-period photosynthesis operator

In all published variants of artificial plant optimisation algorithm, the light response curve of photosynthesis operator is always fixed. It is confused with natural phenomenon because generally, different plants may require different light response curves. Therefore, in this paper, we select seven general models: parabola model, exponential curve model2, exponential curve model1, non-rectangular hyperbolic model, updated rectangular hyperbolic model, rectangular hyperbolic model and straight line model, to investigate the performance of the combination of several light response curves. The details of these models are listed as follows (Ye and Yu, 2007):

1 Parabola model:

$$P_n(I) = -2.0011 \times 10^{-5} I^2 + 0.0344I - 0.57$$

2 Exponential curve model2:

$$P_n(I) = 0.045I - 0.241$$

3 Exponential curve model1:

$$P_n(I) = 19.802(1 - 1.008e^{-0.003I})$$

4 Non-rectangular hyperbolic model:

$$P_n(I) = \frac{0.068I + 43.05 - \sqrt{(0.068I + 43.05)^2 - 9.204I}}{1.572} + 1.09$$

5 Updated rectangular hyperbolic model:

$$P_n(I) = 0.049I \cdot \frac{1 - 1.1052 \times 10^{-4} I}{1 + 0.0021I} + 1.38$$

6 Rectangular hyperbolic model:

$$P_n(I) = \frac{2.113 \cdot I}{0.065 \cdot I + 32.5} + 2.04$$

7 Straight line model:

$$P_n(I) = 23.27(1 - e^{0.002I}) + 1.15$$

We adopt the orthogonal experimental design to decide the best hybridisation of models. In each test, each model can be selected (noted as 1) or omitted (noted as 0). In this paper, the following orthogonal table $L_8(2^7)$ is used to test.

Table 2 Orthogonal Table $L_8(2^7)$

Test	*Mod.1*	*Mod.2*	*Mod.3*	*Mod.4*	*Mod.5*	*Mod.6*	*Mod.7*
1	1	1	1	1	1	1	1
2	1	1	1	0	0	0	0
3	1	0	0	1	1	0	0
4	1	0	0	0	0	1	1
5	0	1	0	1	0	1	0
6	0	1	0	0	1	0	1
7	0	0	1	1	0	0	1
8	0	0	1	0	1	1	0

Symbol $Mod.1$, $Mod.2$, ..., $Mod.7$ represent the above mentioned seven model: rectangular hyperbolic model, non-rectangular hyperbolic model, updated rectangular hyperbolic model, parabola model, straight line model and two exponential curve models, respectively. According to this table, we will make eight tests, and for each test, the hybrid models are not the same. For example, in test 1, all seven models are employed, as well as in test 8, only exponential curve model1, updated rectangular hyperbolic model and rectangular hyperbolic model are employed.

The experiments are designed as follows: if m models are employed, then the total evolutionary process is equally divided into m parts, in first part, the first employed light response curve model is used, as well as in the second part, the second employed light response curve is used, similarly, other models are used, especially, in the last part, the last employed light response curve is used. In tests, Rosenbrock, Rastrigin, Ackley and Griewank are used to test (more details can be found in the last section), the population is 100, and the dimension is 30, total evolutionary generation is 1500, and each test run 30 times.

Table 3 Test results for Rosenbrock

Test	*Mean*	*STD*
1	2.8924e+001	7.8475e-002
2	2.8902e+001	9.2628e-002
3	2.8887e+001	9.0329e-002
4	2.8899e+001	9.6012e-002
5	2.8920e+001	7.7763e-002
6	2.8889e+001	8.7050e-002
7	2.8909e+001	8.3797e-002
8	2.8928e+001	7.9800e-002

Table 4 Test results for Rastrigin

Test	*Mean*	*STD*
1	1.1636e-007	1.18084e-007
2	4.3070e-008	8.1278e-008
3	7.6150e-008	1.0270e-007
4	8.70074e-008	1.18084e-007
5	9.3164e-008	1.2544e-007
6	5.9421e-008	7.7773e-008
7	6.7763e-008	9.7646e-008
8	2.4238e-007	5.1947e-007

Table 5 Test results for Ackley

Test	*Mean*	*STD*
1	6.4168e-005	6.6399e-005
2	6.3336e-005	6.9110e-005
3	7.9863e-005	7.0224e-005
4	7.5804e-005	6.6399e-005
5	6.1892e-005	5.2889e-005
6	5.6692e-005	5.7767e-005
7	8.0713e-005	7.4611e-005
8	7.1725e-005	5.8124e-005

Table 6 Test results for Griewank

Test	*Mean*	*STD*
1	5.4435e-005	2.0583e-007
2	8.0170e-008	1.5441e-007
3	1.0542e-007	1.3216e-007
4	1.1906e-007	2.0583e-007
5	6.2670e-008	1.0608e-007
6	5.61496e-008	7.9534e-008
7	8.5238e-008	1.6737e-007
8	1.3678e-007	2.5421e-007

According to the test results (see Tables 3–6), Test 4 achieves the best performance than other seven tests. Therefore, the total evolutionary process will be divided into three parts, and the corresponding light responsive curve models are parabola model, updated rectangular hyperbolic model and straight line model. The pseudo code of this new photosynthesis operator is listed as follows:

Algorithm 5 Three-period Photosynthesis Operator ()

```
1: For i = 1 to m, do
2: If iteration < MAXITER/3 do
3: Selecting parabola model as light responsive curve
4: Else if iteration < 2·MAXITER/3 do
5: Selecting updated rectangular hyperbolic model
   as light responsive curve
6: Else
7: Selecting straight line model as light
   responsive curve
8: End if
9: End do
```

Because this new variant divides the whole evolutionary process into three parts for photosynthesis operator, therefore, we call it as APOA with three-period photosynthesis (APOA-TP, in briefly).

4 Simulation results

To test the performance, we select four famous benchmarks: Rosenbrock, Rastrigin, Ackley and Griewank. All of them are multi-modal functions, more details can refer to the corresponding references.

- Rosenbrock function:

$$f_1(x) = \sum_{j=1}^{n-1}[100(x_{j+1} - x_j^2)^2 + (x_j - 1)^2]$$

where $|x_j| \leq 30.0$, and

$$f_1(x^*) = f_1(0, 0, ..., 0) \approx 0$$

- Rastrigin function:

$$f_2(x) = \sum_{j=1}^{n}[x_j^2 - 10\cos(2\pi x_j) + 10]$$

where $|x_j| \leq 5.12$, and

$$f_2(x^*) = f_2(0, 0, ...0,) \approx 0.0$$

- Ackley function:

$$f_3(x) = -20exp(-0.2\sqrt{\frac{1}{n}\sum_{j=1}^{n} x_j^2})$$
$$-exp(\frac{1}{n}\sum_{k=1}^{n}\cos 2\pi x_k) + 20 + e$$

where $|x_j| \leq 32.0$, and

$$f_3(x^*) = f_3(0, 0, ..., 0) = 0.0$$

- Griewank function:

$$f_4(x) = \frac{1}{4000}\sum_{j=1}^{30} x_j^2 - \prod_{j=1}^{30}\cos(\frac{x_j}{\sqrt{j}}) + 1$$

where $|x_j| \leq 600.0$, and

$$f_4(x^*) = f_4(0, 0, ..., 0) = 0 \quad (9)$$

To provide a comparison, the standard version of APOA is employed to compare. For each experiment, the simulation records the mean value (Mean) and the standard deviation (STD). For the parameter setting of APOA and APOA-TP, please refer to Cai et al. (2012). To certify the high-dimension capability, the problem dimensionality is varying from 30 to 300, and all comparison results are showed in Tables 7 to 10. It is obviously that APOA-TP is better than APOA especially for high-dimension cases.

5 Conclusions

As a new methodology, there are many research topics for artificial plant optimisation algorithm. Photosynthesis operator is one important operator used to produce energy. In this paper, we propose one hybrid operator including three different light responsive curves. Simulation results show it is effective.

Table 7 Comparison results for Rosenbrock

Dim.	*Alg.*	*Mean*	*STD*
30	APOA	2.8919e+01	7.2839e–02
	APOA-TP	2.8874e+01	7.8327e–02
50	APOA	4.8904e+01	9.4121e–02
	APOA-TP	4.8857e+01	7.7553e–02
100	APOA	9.8902e+01	8.3264e–02
	APOA-TP	9.8890e+01	8.7327e–02
150	APOA	1.4891e+02	8.4547e–02
	APOA-TP	1.4891e+02	7.5695e–02
200	APOA	1.9989e+02	7.4440e–02
	APOA-TP	1.9889e+02	8.0360e–02
250	APOA	2.4891e+02	8.0698e–02
	APOA-TP	2.4886e+02	7.3697e–02
300	APOA	2.9891e+02	7.4061e–02
	APOA-TP	2.9888e+02	7.6978e–02

Table 8 Comparison results for Rastrigin

Dim.	*Alg.*	*Mean*	*STD*
30	APOA	3.4551e–08	6.4800e–08
	APOA-TP	1.1431e–08	2.3045e–08
50	APOA	1.8692e–08	4.9251e–08
	APOA-TP	6.0158e–09	1.5724e–08
100	APOA	4.5446e–09	7.8716e–09
	APOA-TP	1.7039e–09	2.8069e–09
150	APOA	2.0051e–09	2.5523e–09
	APOA-TP	4.5767e–10	7.9690e–10
200	APOA	1.7673e–09	3.4377e–09
	APOA-TP	2.5045e–10	6.3177e–10
250	APOA	3.3044e–08	6.8492e–08
	APOA-TP	8.4258e–09	2.0731e–08
300	APOA	1.0507e–09	2.0127e–09
	APOA-TP	2.1305e–10	3.9896e–10

Table 9 Comparison results for Ackley

Dim.	*Alg.*	*Mean*	*STD*
30	APOA	8.2679e–005	8.0141e–005
	APOA-TP	2.6617e–005	2.9989e–005
50	APOA	2.7542e–005	2.0214e–005
	APOA-TP	1.5276e–005	1.1705e–005
100	APOA	1.0961e–005	1.8624e–005
	APOA-TP	3.0064e–006	3.2822e–006
150	APOA	4.2604e–006	3.7620e–006
	APOA-TP	2.2006e–006	2.5310e–006
200	APOA	4.4306e–006	3.2532e–006
	APOA-TP	1.5574e–006	1.3616e–006
250	APOA	2.4997e–006	2.4753e–006
	APOA-TP	1.5041e–006	1.4152e–006
300	APOA	1.7613e–006	1.4255e–006
	APOA-TP	7.6839e–007	7.0935e–007

Table 10 Comparison results for Griewank

Dim.	*Alg.*	*Mean*	*STD*
30	APOA	9.4572e–008	1.5072e–007
	APOA-TP	6.1677e–009	8.1343e–009
50	APOA	2.3322e–008	2.9811e–008
	APOA-TP	3.9127e–009	6.3959e–009
100	APOA	1.0892e–009	1.5613e–009
	APOA-TP	2.6849e–010	4.1389e–010
150	APOA	4.37413e–010	6.5850e–010
	APOA-TP	7.6289e–011	1.1095e–010
200	APOA	1.7851e–010	2.6843e–010
	APOA-TP	5.0423e–011	1.6071e–010
250	APOA	4.7548e–011	1.1528e–010
	APOA-TP	8.6481e–012	1.4256e–011
300	APOA	1.1660e–010	1.7043e–010
	APOA-TP	1.1429e–011	2.2128e–011

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