Research Article

Accelerated Particle Swarm Optimization to Solve Large-Scale Network Plan Optimization of Resource-Leveling with a Fixed Duration

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Large-scale network plan optimization of resource-leveling with a fixed duration is challenging in project management. Particle swarm optimization (PSO) has provided an effective way to solve this problem in recent years. Although the previous algorithms have provided a way to accelerate the optimization of large-scale network plan by optimizing the initial particle swarm, how to more effectively accelerate the optimization of large-scale network plan with PSO is still an issue worth exploring. The main aim of this study was to develop an accelerated particle swarm optimization (APSO) for the large-scale network plan optimization of resource-leveling with a fixed duration. By adjusting the acceleration factor, the large-scale network plan optimization of resource-leveling with a fixed duration yielded a better result in this study than previously reported. Computational results demonstrated that, for the same large-scale network plan, the proposed algorithm improved the leveling criterion by 24% compared with previous solutions. APSO proposed in this study was similar in form to, but different from, particle swarm optimization with contraction factor (PSOCF). PSOCF did not have as good adaptability as APSO for network plan optimization. Accelerated convergence particle swarm optimization (ACPSO) is similar in form to the APSO proposed in this study, but its irrationality was pointed out in this study by analyzing the iterative matrix convergence.

1. Introduction

The network plan is considered by the engineering community as a promising management method. A large-scale network plan with many works (such as more than 50) is an effective tool for solving large project management problems [1, 2]. However, the number of possible solutions in large-scale network plan optimization sharply increases with the number of works, and the time of calculation is exponential, far beyond the processing capacity of computing resources, so mathematics and computer science cannot solve the problem known as NP problem [2, 3]. In recent years, genetic algorithm [4, 5], Monte Carlo partition optimization [6], and particle swarm optimization (PSO) [7, 8] have provided an effective means to solve this problem.

PSO was proposed in 1995. Although the convergence of PSO is still controversial, its applied research has shown good

results [9–13]. Experimental research includes optimization, biomedicine, communication, control, and so forth. Theoretical research includes PSO improvement, parameter selection, stability, convergence, and so forth. Improvement in performance of PSO reported in the literature included adjusting the parameters of PSO (inertial factor) [14–17], adopting the neighborhood topology [18], and combining with other algorithms (genetic algorithm, simulated annealing algorithm, and differential evolution algorithm) [19–22]. It does not include the solution to large-scale network plan optimization problems.

Accelerated optimization can be marked by better-optimized solutions with the same number of iterations for iterative optimization. Yang et al. introduced some virtual particles in random directions with random amplitude to enhance the explorative capability of particles in PSO [23]; Qi et al. hybridized an improved estimation of distribution

algorithm (EDA) using historic best positions to construct a sample space with PSO both in sequential and in parallel to improve population diversity control and avoid premature convergence for optimization of a water distribution network [24]; Zhang et al. added the random velocity operator from local optima to global optima into the velocity update formula of constriction particle swarm optimization (CPSO) to accelerate the convergence speed of the particles to the global optima and reduce the likelihood of being trapped into local optima [25]; Zhou et al. adjusted random functions with the density of the population so as to manipulate the weight of cognition part and social part and executed mutation on both personal best particle and group best particle to explore new areas [26]. Zhang and Yang accelerated the optimization of large-scale network plan resources and analyzed the acceleration optimization mechanism via stochastic process by optimizing the initial particle swarm using the Monte Carlo method under limiting conditions [7, 8, 27]; Ren and Wang proposed a PSO algorithm with accelerated convergence, theoretically proved the fast convergence of the algorithm, and optimized the parameters in the algorithm [28].

Inspired by previous efforts [28] to accelerate the convergence of PSO algorithm, this study proposed the method for the large-scale network plan optimization of resource-leveling with a fixed duration through debugging acceleration coefficient (it might also be described as accelerated PSO, or APSO for short) and yielded a better solution than reported in the previous literature.

This paper is organized as follows. Section 2 describes the experimental research of the large-scale network plan optimization of resource-leveling with a fixed duration using APSO. Section 3 analyzes the difference between APSO and PSO with a contraction factor (PSOCF) [29]. Section 4 analyzes the irrationality of accelerated convergence PSO (ACPSO) reported in [28].

2. APSO to Solve the Large-Scale Network Plan Optimization of Resource-Leveling with a Fixed Duration

Large-scale network plan optimization of resource-leveling with a fixed duration achieved the balance of resource demand in each period during the entire period of the project. Equilibrium could be marked by the variance of resources. The formula used to calculate the variance was as follows: $\sigma^2 = (\sum_{i=1}^J (x_i - \mu)^2) / J$ where the total number of samples x_i is J , and the arithmetic mean of x_i is μ . The smaller the variance, the more balanced the resource.

The evolutionary equation of basic PSO was as follows:

$$\begin{aligned} v_{ij}(t+1) &= wv_{ij}(t) + c_1 \text{rand}_1(t) (p_{gj}(t) - x_{ij}(t)) \\ &\quad + c_2 \text{rand}_2(t) (p_g(t) - x_{ij}(t)) \\ x_{ij}(t+1) &= x_{ij}(t) + v_{ij}(t+1), \end{aligned} \quad (1)$$

where t is the number of iterations; $x_{ij}(t+1)$ is j -dimension space coordinates of particle i in $t+1$ iteration; $x_{ij}(t)$ is j -dimension space coordinates of particle i in t iteration; w is

inertial factor, usually taking the value of 1 according to the experience; $v_{ij}(t)$ is the j -dimension flight speed of particle i ; c_1 and c_2 are accelerators evaluated usually between 0 and 2 by experience; rand_1 and rand_2 are random functions of value in the range of $[0, 1]$; $p_{gj}(t)$ is the best place to be experienced by particle j ; and $p_g(t)$ is the best place for all particles to experience. The convergence condition was adopted by setting maximum iteration times G .

The evolutionary equation of accelerated PSO (APSO) was as follows:

$$\begin{aligned} v_{ij}(t+1) &= a (wv_{ij}(t) + c_1 \text{rand}_1(t) (p_{gj}(t) - x_{ij}(t)) \\ &\quad + c_2 \text{rand}_2(t) (p_g(t) - x_{ij}(t))) \\ x_{ij}(t+1) &= x_{ij}(t) + v_{ij}(t+1), \end{aligned} \quad (2)$$

where a is the acceleration coefficient, and the other signs are the same as earlier. The evolution equation of accelerated particle swarm algorithm has one more a than with that of the basic PSO algorithm and one more w than that of the particle swarm algorithm with contraction factor. However, it has produced significant results for solving large-scale network plan optimization of resource-leveling with a fixed duration as follows.

For example, a large network plan with 223 works is the same as Figure 1 in [27]. The debugging results of change a are shown in Table 1, where the variance of the corresponding optimization results is 17.58 (better than the variance 22.99 quoted in [27]). The start time of each work is shown in Table 2, and the resource requirements of each unit time are shown in Table 3.

As shown in Table 1, for $w = 1$, $c_1 = c_2 = 2.05$, the number of particles 50, and $G = 100$, the minimum variance 17.58 could be obtained by adjusting the acceleration coefficient a , which was significantly optimized compared with the variance quoted in [27] without the acceleration coefficient (that is 22.99). For $w = 1$, $c_1 = 3.5$, $c_2 = 0.4$, the number of particles 50, and $G = 100$, the minimum variance 18.4 could be obtained by adjusting the acceleration coefficient a , which was significantly optimized compared with the variance quoted in the literature [27]. For $w = 0.8$, $c_1 = c_2 = 2.05$, the number of particles 50, and $G = 100$, the minimum variance 18.93 could be obtained by adjusting the acceleration coefficient a , which was significantly optimized compared with the variance quoted in [27]. For $w = 0.729$, $c_1 = c_2 = 1.454$, the number of particles 50, and $G = 100$, variance smaller than 17.83 (acceleration coefficient 1) could not be obtained by adjusting the acceleration coefficient a .

3. Difference between APSO and PSOCF [29]

APSO proposed in this study was similar in form to PSOCF. The evolution equation of PSOCF was as follows [29]:

$$\begin{aligned} v_{ij}(t+1) &= \eta (v_{ij}(t) + c_1 \text{rand}_1(t) (p_{gj}(t) - x_{ij}(t)) \\ &\quad + c_2 \text{rand}_2(t) (p_g(t) - x_{ij}(t))) \\ x_{ij}(t+1) &= x_{ij}(t) + v_{ij}(t+1), \end{aligned} \quad (3)$$

TABLE 1: Optimization parameter's debugging results of the large-scale network plan optimization of resource-leveling with a fixed duration using the accelerated particle swarm algorithm (particle number is 50; $G = 100$).

sequence number	w	c_1	c_2	a	σ^2
1	1	2.05	2.05	1	23.97
2	1	2.05	2.05	0.33	19.31
3	1	2.05	2.05	0.31	18.97
4	1	2.05	2.05	0.3	17.58
5	1	2.05	2.05	0.29	18.61
6	1	2.05	2.05	3	31.43
7	1	2.05	2.05	0.1	31.39
8	1	2.05	2.05	0.03	31.43
9	1	3.5	0.4	1	22.99
10	1	3.5	0.4	0.03	31.43
11	1	3.5	0.4	0.5	21.4
12	1	3.5	0.4	0.8	31.43
13	1	3.5	0.4	0.3	23.02
14	1	3.5	0.4	0.6	16.35 error
15	1	3.5	0.4	0.4	20.8
16	1	3.5	0.4	0.35	19.9
17	1	3.5	0.4	0.33	18.4
18	1	3.5	0.4	0.31	25.5
19	0.8	2.05	2.05	1	24.53
20	0.8	2.05	2.05	0.3	31.43
21	0.8	2.05	2.05	1.2	31.43
22	0.8	2.05	2.05	0.4	31.43
23	0.8	2.05	2.05	0.5	31.00
24	0.8	2.05	2.05	0.6	25.85
25	0.8	2.05	2.05	0.7	18.93
26	0.8	2.05	2.05	0.8	22.38
27	0.729	1.454	1.454	1	17.83
28	0.729	1.454	1.454	0.8	25.00
29	0.729	1.454	1.454	1.05	20.54
30	0.729	1.454	1.454	0.9	18.33 error

Note. The value in italics is the optimal value under certain parameter conditions.

where contraction factor $\eta = 2\kappa/|2-\varphi-\sqrt{\varphi(\varphi-4)}|$, $\kappa \in [0, 1]$, $\varphi = c_1 + c_2$. The other signs are the same as earlier.

For $c_1 = 3.5$, $c_2 = 0.4$, $\eta = 2\kappa/|2-\varphi-\sqrt{\varphi(\varphi-4)}| = 2\kappa/|2-3.9-\sqrt{3.9(3.9-4)}|$ does not exist. The PSOCF could not be used, but APSO in this study was used for optimization of network plan and the results were good, as shown in Table 1.

For $c_1 = 2.05$, $c_2 = 2.05$, $\eta = 2\kappa/|2-\varphi-\sqrt{\varphi(\varphi-4)}| = 2(0 \sim 1)/|2-4.1-\sqrt{4.1(4.1-4)}| = 0 \sim 0.73$. The acceleration factor a is outside the scope of the contraction factor η , and the optimization of APSO in this study was performed as usual, as shown in Table 1.

Thus, although, in this study, APSO was similar in form to PSOCF, essentially, for network plan optimization, PSOCF did not have as good adaptability as APSO.

4. Irrationality of ACPSO Reported in [28]

APSO proposed in this study was inspired by the ACPSO algorithm quoted in [28]. APSO was similar in form to

ACPSO. The evolution equation of ACPSO algorithm proposed in [28] was as follows:

$$\begin{aligned}
 v_{ij}(t+1) &= (\sin(\alpha))^\beta (wv_{ij}(t) \\
 &+ c_1 \text{rand}_1(t) (p_{gj}(t) - x_{ij}(t)) \\
 &+ c_2 \text{rand}_2(t) (p_g(t) - x_{ij}(t))) \\
 x_{ij}(t+1) &= (\sin(\alpha))^\beta x_{ij}(t) + v_{ij}(t+1),
 \end{aligned} \tag{4}$$

where α is angle value with a distinct optimization effect when its value is within $[0, \pi/8]$; β is a constant greater than zero, and the optimization effect is good when the value is 3. The other signs are the same as earlier.

The ACPSO algorithm quoted in [28] was based on one inference: PSO is iterative. The iterative converges when the spectral radius of iterative matrix L (that is the maximum absolute value of the matrix eigenvalue) is less than 1. The smaller the spectral radius of L , the faster the iteration

TABLE 2: The parameters and their optimization solution for the optimization example of the resource-leveling with a fixed duration.

Number	Work	Duration	Resource Quantity	ES	Optimized ES
1	1-3	2	2	0	0
2	1-4	2	1	0	0
3	3-4	2	1	2	2
4	1-2	1	2	0	0
5	4-6	4	1	4	3
6	5-8	4	1	7	7
7	5-9	5	1	7	8
8	6-8	5	3	13	13
9	7-8	8	3	15	15
10	3-6	3	2	2	3
11	2-4	3	2	1	1
12	3-5	5	1	2	2
13	2-8	3	2	1	1
14	5-6	6	2	7	6
15	2-6	1	3	1	1
16	6-7	2	0	13	12
17	8-9	7	3	23	22
18	8-11	2	2	23	25
19	8-10	2	1	23	23
20	7-10	2	1	15	15
21	9-10	1	2	30	29
22	9-12	4	1	30	28
23	18-19	8	3	57	57
24	17-20	2	1	51	52
25	16-19	4	1	49	48
26	18-21	5	1	57	58
27	17-19	5	3	51	51
28	16-17	2	2	49	49
29	15-17	2	1	46	46
30	14-18	2	1	42	41
31	14-17	1	2	42	41
32	13-15	2	1	44	44
33	10-11	4	1	31	30
34	12-13	5	1	39	39
35	10-13	5	3	31	30
36	10-12	8	3	31	30
37	17-18	6	0	51	51
38	15-16	3	2	46	46
39	11-15	5	1	35	34
40	14-15	3	2	42	41
41	11-17	5	1	35	35
42	12-14	3	2	39	38
43	11-13	6	2	35	34
44	12-15	2	0	39	38
45	21-22	2	2	70	69
46	22-24	2	1	75	88
47	20-22	2	1	73	85
48	20-24	1	2	73	85
49	20-26	2	1	73	84

TABLE 2: Continued.

Number	Work	Duration	Resource Quantity	ES	Optimized ES
50	19-21	5	1	65	64
51	19-22	5	3	65	65
52	19-20	8	3	65	76
53	24-25	3	2	77	90
54	24-26	5	1	77	96
55	26-27	3	2	85	101
56	25-26	5	1	80	93
57	23-27	3	2	72	99
58	23-26	6	2	72	70
59	23-24	1	3	72	71
60	21-23	2	0	70	69
61	21-24	7	3	70	70
62	3-28	1	2	2	2
63	3-30	3	2	2	2
64	3-31	1	3	2	3
65	28-30	2	1	3	3
66	28-29	2	2	3	3
67	29-30	2	1	5	5
68	29-31	3	2	5	5
69	29-34	3	2	5	5
70	30-31	4	1	7	8
71	5-31	6	2	7	7
72	5-34	5	3	7	7
73	31-32	2	0	13	14
74	31-34	4	1	13	12
75	32-33	2	1	15	16
76	32-34	8	3	15	16
77	9-34	7	3	30	29
78	9-33	2	1	30	29
79	34-35	2	2	44	44
80	33-34	1	2	43	43
81	33-35	8	3	43	44
82	33-36	5	3	43	42
83	12-33	4	1	39	39
84	12-36	6	2	39	37
85	12-37	5	1	39	37
86	35-36	5	1	51	53
87	35-37	2	0	51	52
88	35-39	5	1	51	53
89	36-37	2	1	56	58
90	14-37	3	2	42	41
91	14-39	2	1	42	41
92	37-38	3	2	58	60
93	37-39	1	2	58	60
94	38-39	2	2	61	63
95	18-39	6	0	57	57
96	18-40	5	3	57	57
97	39-40	8	3	63	77
98	39-41	2	1	63	66
99	40-41	5	1	78	86

TABLE 2: Continued.

Number	Work	Duration	Resource Quantity	ES	Optimized ES
100	40-42	5	3	78	84
101	21-40	8	3	70	70
102	21-42	2	1	70	69
103	21-43	1	2	70	69
104	41-42	2	2	83	92
105	41-43	7	3	83	91
106	41-45	2	1	83	91
107	42-43	2	1	85	95
108	23-43	1	3	72	72
109	23-45	5	1	72	72
110	43-44	3	2	90	98
111	43-45	6	2	90	98
112	44-45	5	1	93	101
113	27-45	3	2	88	104
114	38-40	4	1	61	63
115	47-48	2	2	8	9
116	48-50	2	1	10	11
117	47-50	2	1	8	9
118	48-49	1	2	10	11
119	50-53	4	1	14	16
120	52-57	4	1	49	49
121	52-58	5	1	49	61
122	53-57	5	3	55	56
123	56-57	8	3	57	59
124	47-53	3	2	8	9
125	49-50	3	2	11	12
126	47-52	5	1	8	8
127	49-57	3	2	11	13
128	52-53	6	2	49	50
129	49-53	1	3	11	12
130	53-56	2	0	55	56
131	57-58	7	3	65	68
132	57-61	2	2	65	68
133	57-59	2	1	65	67
134	56-59	2	1	57	58
135	58-59	1	2	72	75
136	58-60	4	1	72	76
137	71-72	8	3	99	102
138	69-75	2	1	93	98
139	68-72	4	1	91	94
140	71-73	5	1	99	103
141	69-72	5	3	93	98
142	68-69	2	2	91	95
143	67-69	2	1	88	92
144	65-71	2	1	84	88
145	65-69	1	2	84	87
146	64-67	2	1	86	90
147	59-61	4	1	73	76
148	60-64	5	1	81	85

TABLE 2: Continued.

Number	Work	Duration	Resource Quantity	ES	Optimized ES
149	59-64	5	3	73	77
150	59-60	8	3	73	77
151	69-71	6	0	93	97
152	67-68	3	2	88	92
153	61-67	5	1	77	80
154	65-67	3	2	84	87
155	61-69	5	1	77	80
156	60-65	3	2	81	85
157	61-64	6	2	77	81
158	60-67	2	0	81	86
159	73-76	2	2	112	115
160	76-79	2	1	117	121
161	75-76	2	1	115	119
162	75-79	1	2	115	118
163	75-83	2	1	115	118
164	72-73	5	1	107	110
165	72-76	5	3	107	110
166	72-75	8	3	107	110
167	79-82	3	2	119	123
168	79-83	5	1	119	123
169	83-84	3	2	127	132
170	82-83	5	1	122	126
171	78-84	3	2	114	118
172	78-83	6	2	114	119
173	78-79	1	3	114	119
174	73-78	2	0	112	116
175	73-79	7	3	112	116
176	46-47	1	2	7	8
177	47-51	3	2	8	9
178	47-54	1	3	8	8
179	46-51	2	1	7	8
180	29-46	2	2	5	6
181	29-51	2	1	5	5
182	29-54	3	2	5	5
183	51-54	4	1	11	12
184	52-54	6	2	49	51
185	34-52	5	3	44	45
186	54-55	2	0	55	57
187	34-54	4	1	44	44
188	55-62	2	1	57	59
189	34-55	8	3	44	43
190	34-58	7	3	44	44
191	58-62	2	1	72	75
192	34-62	1	2	44	45
193	35-62	8	3	51	52
194	62-63	5	3	85	90
195	60-62	4	1	81	86
196	60-63	6	2	81	85
197	60-66	2	1	81	86

TABLE 2: Continued.

Number	Work	Duration	Resource Quantity	ES	Optimized ES
198	35-63	5	1	51	53
199	35-66	2	0	51	52
200	63-66	2	1	90	95
201	65-66	3	2	84	88
202	39-65	2	1	63	64
203	66-70	3	2	92	97
204	39-66	1	2	63	65
205	39-70	2	2	63	66
206	39-71	6	0	63	66
207	71-74	5	3	99	103
208	39-74	8	3	63	64
209	41-74	5	1	83	92
210	74-77	5	3	120	120
211	73-74	8	3	112	112
212	73-77	2	1	112	115
213	73-80	1	2	112	115
214	41-77	2	2	83	92
215	41-80	7	3	83	91
216	77-80	2	1	125	125
217	78-80	1	3	114	118
218	45-78	5	1	98	107
219	80-81	3	2	127	127
220	45-80	6	2	98	108
221	81-84	5	1	130	130
222	45-84	3	2	98	107
223	70-74	4	1	95	100

Note. "ES" is the early start time of each work. "Optimized ES" is the start time optimized.

TABLE 3: The resource requirements of each unit time of large-scale network plan optimization of resource-levelling with a fixed duration using accelerated particle swarm algorithm (duration is 135).

unit time	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
resource requirements	5	10	10	17	9	12	17	16	17	19	18	14	12	9	9	11	12
unit time	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
resource requirements	11	7	7	6	6	9	7	4	5	5	3	4	7	12	11	10	10
unit time	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51
resource requirements	12	10	7	10	9	10	7	13	13	13	16	21	19	16	15	16	15
unit time	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68
resource requirements	12	12	14	13	13	11	15	15	19	18	13	10	10	15	15	14	11
unit time	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85
resource requirements	13	16	17	17	15	12	12	12	13	17	14	14	14	16	13	13	14
unit time	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100	101	102
resource requirements	14	14	15	15	12	12	13	20	18	14	13	14	11	11	13	11	11
unit time	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119
resource requirements	12	13	10	10	9	10	8	8	10	10	12	12	10	11	12	9	14
unit time	120	121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	
resource requirements	15	11	9	9	8	8	4	3	4	3	3	2	1	3	3	3	

converges. The absolute value of the eigenvalues of L is as follows: $|\lambda_{1,2}| = |1 + w - (c_1 + c_2)/2 \pm ((-1 - w + (c_1 + c_2)/2)^2 - 4w)^{1/2}/2|$, where $\sqrt{(-1 - w + (c_1 + c_2)/2)^2 - 4w} \geq 0$. The reasoning was problematic, and the analysis was as follows.

The evolution equation of PSO can be written in the matrix form:

$$\begin{bmatrix} v(t+1) \\ x(t+1) \end{bmatrix} = A_t \begin{bmatrix} v_t \\ x_t \end{bmatrix} + \begin{bmatrix} \varphi_1 & \varphi_2 \\ \varphi_1 & \varphi_2 \end{bmatrix} \begin{bmatrix} p_{i,t} \\ p_{g,t} \end{bmatrix}, \quad (5)$$

where $A_t = \begin{bmatrix} w & -\varphi \\ w & 1-\varphi \end{bmatrix}$, $\varphi = \varphi_1 + \varphi_2 = c_1 r_1 + c_2 r_2$, $p_{i,t}$ is the best place ever found, and $p_{g,t}$ is the best location for the whole particle swarm to date. The other signs are the same as earlier.

Set,

$$y(t) = \begin{bmatrix} v(t) \\ x(t) \end{bmatrix}, \quad (6)$$

$$\phi_t = \begin{bmatrix} \varphi_1 p_{i,t} + \varphi_2 p_{g,t} \\ \varphi_1 p_{i,t} + \varphi_2 p_{g,t} \end{bmatrix}.$$

Then, (5) can be changed to

$$y(t+1) = A_t y(t) + \phi_t. \quad (7)$$

E is the mathematical expectation.

$$\begin{aligned} E(y(t+1)) &= \begin{bmatrix} E(v(t+1)) \\ E(x(t+1)) \end{bmatrix}, \\ E(A_t) &= \begin{bmatrix} w & -\frac{c_1+c_2}{2} \\ w & 1-\frac{c_1+c_2}{2} \end{bmatrix}, \\ E(\phi_t) &= \begin{bmatrix} \frac{c_1 E(p_{i,t}) + c_2 E(p_{g,t})}{2} \\ \frac{c_1 E(p_{i,t}) + c_2 E(p_{g,t})}{2} \end{bmatrix}. \end{aligned} \quad (8)$$

Set $Q_{t+1} = E(y(t+1))$, $M = E(A_t)$, $Z = E(\phi_t)$. The characteristic value of M is

$$\begin{aligned} \lambda_{1,2} &= \frac{1 + w - (c_1 + c_2)/2 \pm \sqrt{(-1 - w + (c_1 + c_2)/2)^2 - 4w}}{2}. \end{aligned} \quad (9)$$

As long as $1 - (c_1 + c_2)/2 \neq -w \pm 2\sqrt{w}$, matrix A is going to be

$$AMA^{-1} = L = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}. \quad (10)$$

Set $AQ_{t+1} = H_t$. It could be deduced that the PSO algorithm was an iteration:

$$H_{t+1} = LH_t + AZ, \quad (11)$$

where L is an iterative matrix.

The following two equations are equivalent to the inference in [30]:

$$\begin{aligned} Ax &= b \\ x &= Bx + g, \end{aligned} \quad (12)$$

where A is the coefficient matrix, x is the unknown column vector, b is a constant number column vector, and g is a constant matrix determined by A and b .

The following iterative matrix B could be obtained by the aforementioned system:

$$x_{k+1} = Bx_k + g. \quad (13)$$

Set x^* as the solution of the system. Then,

$$x^* = Bx^* + g. \quad (14)$$

The aforementioned two formulas (13) and (14) on subtraction yield

$$\begin{aligned} x_{k+1} - x^* &= B(x_k - x^*) = B(B(x_{k-1} - x^*)) \\ &= B^2(x_{k-1} - x^*) = \dots = B^{k+1}(x_0 - x^*). \end{aligned} \quad (15)$$

Because $x_0 - x^*$ has nothing to do with k , $\lim_{k \rightarrow \infty} (x_{k+1} - x^*) = 0$ is equivalent to $\lim_{k \rightarrow \infty} B^{k+1} = 0$. The theorem quoted in [30] shows $\lim_{k \rightarrow \infty} B^{k+1} = 0$ equivalent to $\rho(B) < 1$, where $\rho(B)$ is the spectral radius of matrix B .

Thus, the iterative matrix did not necessarily converge. Because the particle swarm algorithm did not have a set of equations to solve Q_{t+1} , the aforementioned reasoning could not be executed using the iterative matrix L convergence.

In Table 1, for $w = 1$, $c_1 = c_2 = 2.05$ (or $c_1 = 3.5$, $c_2 = 0.4$), the number of particles 50, and $G = 100$, the acceleration coefficient $a = (\sin(\alpha))^\beta = \sin(\pi/10)^3 = 0.03$ reflects the fact that the optimization of ACP SO in [28] was poor. This was the experimental verification of the problems of ACP SO quoted in [28].

5. Conclusions

This study proposed the method for the large-scale network plan optimization of resource-leveling with a fixed duration through adjusting the coefficient of APSO based on the algorithm quoted in [27] to obtain a better solution than previously reported. In other words, for the same large-scale network plan, the proposed algorithm improved the leveling criterion by 24% compared with previous solutions. Thus, the resource variances of 1758 and 223 of a large-scale network plan are the best results for the large-scale network plan optimization of resource-leveling with a fixed duration to date in the literature.

Section 3 discusses the difference between APSO proposed in this study and PSOCF quoted in [29]. The proposed APSO was similar in form to PSOCF, but, essentially, PSOCF did not have as good adaptability as APSO for the network plan optimization.

Section 4 describes the difference between APSO proposed in this study and ACP SO quoted in [28]. Through

analyzing the iterative matrix convergence of equations, it was pointed out that the derivation of iterative matrix convergence of ACPSO algorithm proposed in [28] was problematic, although it experimentally proved APSO was similar in form to ACPSO.

The effect of the APSO proposed in this study was verified to be obvious experimentally. However, the internal working mechanism of APSO is still a core issue worth investigation.

Data Availability

Data generated by the authors or analyzed during the study are available from the following options: (1) Data generated or analyzed during the study are available from the corresponding author by request. (2) All data generated or analyzed during the study are included in the published paper.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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