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Research Article

Maintenance and Operation Optimization Algorithm of PV Plants under Multiconstraint Conditions

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With the rapid increase in the photovoltaic (PV) plants, the real-time operation and maintenance of photovoltaic power generation equipment is very important. The maintenance and dispatching of decentralized power stations is still one of the key issues affecting the operation safety of photovoltaic power stations. However, most of the photovoltaic power stations in China fail to rationally optimize the utilization of resources and time. The current study puts forward effort implementation via genetic algorithm-based multiconstrained optimization methodology. The proposed study optimally overrides the traditional PV plant operation and maintenance dispatching operations with automation and reliability. The proposed study is also applicable to multiple PV plants, multiple maintainers, multipoint departure, different dispatching conditions, and cost considerations. We propose an MOOA algorithm to solve this issue, and we strongly believe that, by defining a suitable fitness function, the convergence speed and optimization ability can be greatly improved, and this study puts a forward step.

1. Introduction

Photovoltaic (PV) power plants are the core component of the smart grid [1, 2]. Because of its dispersed geographical location, complex structure, large number of equipment, and *t* complicated daily operation and maintenance procedures [3, 4], all these routine operations greatly affect the smooth operation of the smart grid. At present, the maintenance of PV plants [5–7] is mainly carried out in accordance with the regular maintenance stipulated by the state. There exist a number of problems which lead to excessive cost maintenance, such as insufficient maintenance, poor reliability, wasting of resources, and increasing maintenance costs. Therefore, operation and maintenance dispatch has become the core problem of an intelligent operation system of PV plants [8, 9]. Operation and maintenance assignment is essentially an extension of the assignment problem. The assignment of n tasks to n persons belongs to balanced assignment; otherwise, it belongs to an unbalanced assignment [10]. In the process of operation and maintenance of PV plants, the number of maintainers is less than that of power plants, which leads to the unbalanced assignment problem. Balanced assignment problem can be well solved by the Hungarian algorithm, eliminating heights and shrinking matrix analysis [11], while unbalanced assignment problem is an objective function optimization problem with constraints, and constraints and objective functions may not be linearized, so it is difficult to solve the problem. A couple of research studies have put forward efforts to solve an unbalanced assignment problem [12, 13], such as dual transportation method [14–17] and fuzzy Hungarian algorithm [18]. However, the solving process is complex and does not have robustness and adaptability. The machine learning especially deep learning also provides a solution to the unbalanced assignment problem [19]. In this paper, a genetic algorithm is presented to solve the unbalanced assignment problem of operation and maintenance dispatch. This method can optimize the operation and maintenance dispatch of multiple PV plants, multiple maintainers, and multipoint departure. It can set different assignment constraints or cost considerations and accelerate the convergence speed and improve the optimization ability of the algorithm.

2. Establishment of Operational and Maintenance Model of PV Plants

The assignment problem takes the matching of tasks and maintainers as the research object to optimize the utilization of resources [20, 21]. The mathematical model of operation and maintenance dispatch for PV plants is described as follows.

Assuming that the number of maintainers is m and the number of tasks is n at a certain time, it obtains $m \leq n$ by considering the maintenance cost, and one plant is only maintained by one maintainer; the maintainers will perform the next task according to the algorithm hints after the accomplishment of last PV plant's maintenance. In this paper, the optimal path of operation and maintenance dispatch is given to minimize the time spent by maintainers on the road. c_{ij} represents the time consuming on the road between two maintained PV plants, i.e.,

$$c_{ij} \geq 0, \quad i = 1, 2, \ldots, m; j = 1, 2, \ldots, n. \tag{1}$$

Then, the mathematical model of multiobjective unbalanced assignment for m maintainers to n PV plants is as follows:

$$\min S_k = \sum_{j=1}^{n} \sum_{i=1}^{m} c_{ij} x_{ij}, \quad i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \quad k = 1, 2, \ldots, p, \tag{2}$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} x_{ij} = 1, i = 1, 2, \ldots, m, \\ \sum_{j=1}^{n} \sum_{i=1}^{m} x_{ij} = n, \quad j = 1, 2, \ldots, n, \\ x_{ij} = 0 \text{ or } 1, \quad i = 1, 2, \ldots, m; j = 1, 2, \ldots, n, \end{cases} \tag{3}$$

where $x_{ij} = 1$ means that the i maintainer completes the j task and $x_{ij} = 0$ means that no task is assigned.

In order to solve the unbalanced assignment in (2), it makes an equivalent exchange for (2), that is, $n - m$ maintainers are added to make up m maintainers. In essence, the added maintainers are only considered in the calculation and will not be shown in dispatch route planning; moreover, the added maintainers will not affect the objective function and constraints, so the essence of the unbalanced assignment problem has not changed. The original unbalanced assignment problem is equivalent to the balanced assignment problem, that is, m maintainers are responsible for the operation and maintenance of n PV plants. The mathematical model is as follows:

$$\min S_k = \sum_{j=1}^{n} \sum_{i=1}^{n} c_{ij} x_{ij}, \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, n; \quad k = 1, 2, \ldots, p, \tag{4}$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} x_{ij} = 1, \quad i = 1, 2, \ldots, n, \\ \sum_{j=1}^{n} \sum_{i=1}^{n} x_{ij} = 1, \quad j = 1, 2, \ldots, n, \\ x_{ij} = 0 \text{ or } 1, \quad i = 1, 2, \cdots, n; j = 1, 2, \ldots, n, \end{cases} \tag{5}$$

where $x_{m+1,1}, x_{m+1,2}, \ldots x_{m+1,n}, \ldots, x_{n,n}$ attributing 0-1 variables correspond to the task assignment of adding maintainers. Obviously, the transformed model is equivalent to the original model. Equation (4) only corresponds to one assignment, which satisfies both constraints and objective optimization. Traditional methods are difficult to solve it. Essentially, the assignment problem of the operation and maintenance of PV plants is an NP-complete problem, which is solved by searching one by one, and time consumed will be $O(n!)$. In this paper, we have employed a genetic algorithm to solve the operation and maintenance dispatch of PV plants.

3. Optimization Algorithm of Maintainers Dispatching

The bases of the genetic algorithm for solving the optimal maintenance strategy of PV plants are as follows: First, the genetic algorithm solves various TSP problems with many results [22–24] and is mature and reliable. Second, the genetic algorithm satisfies the solution of different problems; for instances, the problem of multipoint departure and multiperson operation and maintenance can be assigned by adjusting the chromosome coding method, and the operation and maintenance strategy with uncertain time constraints and cost calculation methods can be made by adjusting the fitness function. Third, the genetic algorithm is easy to iterate, which meets the new demands emerging from the operation and maintenance environment of actual PV plants [25, 26].

As shown in Figure 1, the fault diagnosis process of PV array is described. This paper designs the optimal distribution of voltage sensors according to the distribution of PV plants by equivalent analysis of the weight matrix. Through regression analysis of state data [27, 28], the location of the fault point is obtained by analyzing the voltage signal detected via the voltage sensor. The fault diagnosis model of PV arrays is designed and carried out. This model classifies the types of fault points [29–31]. Based on the concept of equipment lifecycle management [32, 33], this paper establishes the equipment status data model, obtains the information of equipment management, establishes the health history of equipment status, refers to the provisions of equipment manufacturers on their design life, effective operation life, maximum allowable life, and the sample

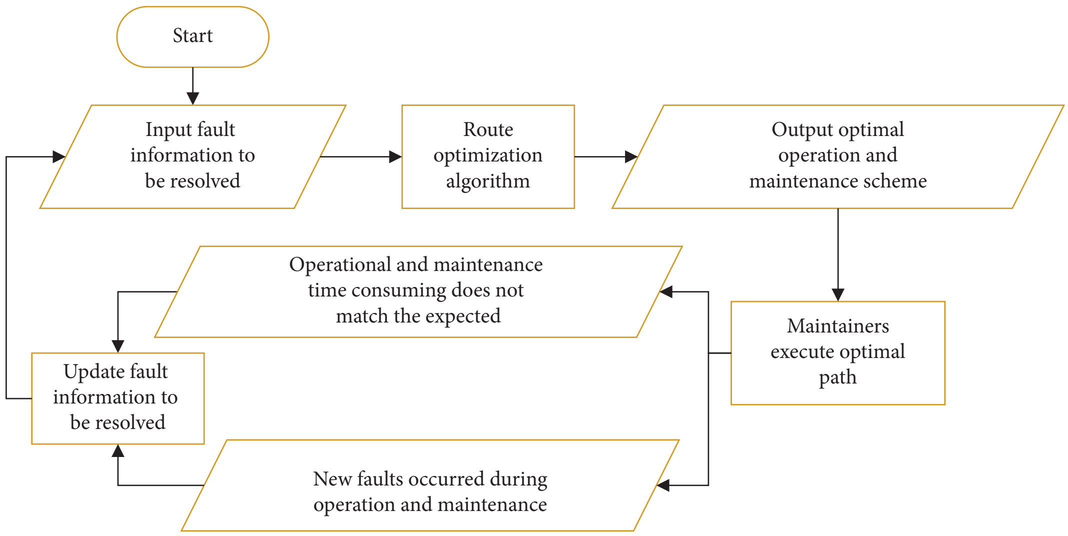

Figure 1: Operation process of fault diagnosis for PV arrays.

statistical data of their actual service life, and achieves the assistant decision making of equipment condition monitoring in photovoltaic power plants.

The following steps are used to optimize the operation and maintenance dispatch of PV plants:

Step 1. Input the fault information to be solved, including the number of faults l, the location of the faulty power station k, the installed capacity of the faulty power station c, the fault grade of the faulty power station g, the remaining maintenance waiting time of the faulty power station t, and the fault flow number s.

Step 2. The path optimization algorithm is obtained by the genetic algorithm.

① Input the traffic cost matrix, that is, the traffic cost between the fault location and the departure location.

② Random sequencing of fault pipeline numbers constitutes the initial gene as follows:

$$\text{gene} = \left[s_{a1},\ s_{a2},\ \cdots,\ s_{an} \right]. \tag{6}$$

③ Repeat ② for N times to form N initial genes: $\text{gene}_1, \text{gene}_2, \ldots, \text{gene}_n$; N initial genes constitute the initial population Q.

④ Construct fitness function $\Psi(\text{gene})$:

$$\begin{aligned}\Psi(\text{gene}) = {} & \frac{a}{\sum_{i=1}^{n-1} C_{s_i,s_{i+1}}} + \frac{b}{\sum_{i=1}^{n} I(s_i) * c_{s_i}} \\ & + \frac{c}{\sum_{i=1}^{n} I(s_i) * g_{s_i}} + \frac{d}{\sum_{i=1}^{n} I(s_i) * t_{s_i}},\end{aligned} \tag{7}$$

where gene represents the gene of fitness function to evaluate fitness, s_i represents the fault flow number in the gene, $C_{s_i,s_{i+1}}$ represents the traffic cost between the two fault locations determined by the fault flow number and the traffic cost matrix C, $\sum_{i=1}^{n-1} C_{s_i,s_{i+1}}$ represents the total traffic cost of maintenance in the order of the intermediate flow number, $I(s_i)$ represents the order of s_i in gene; $I(s_i) = 1$, if it ranks first in gene. c_{s_i} denotes the installed capacity of the faulty power station corresponding to the fault pipeline number s_i, g_{s_i} denotes the fault grade of the faulty plant corresponding to the fault pipeline number s_i, and t_{s_i} denotes the remaining maintenance waiting time of the faulty power station corresponding to the fault pipeline number s_i. a represents the penalty coefficient of the traffic cost; the default is 1000; the larger m is, the lower the route of the traffic cost will be preferred, and b represents the penalty coefficient of the installed capacity; the default is 100; the larger b is, the preferred choice will be made. For a power station with large installed capacity, c means the penalty coefficient of the fault grade. The bigger c is, the higher the penalty coefficient of maintenance time will be. d means the penalty coefficient of maintenance time. The bigger d is, the lower the waiting time of maintenance will be.

⑤ n_1 individuals were randomly selected from the population Q, and the probability of individual gene_i being selected was as follows:

$$P_i = \frac{\Psi(\text{gene}_i)}{\text{sum}(\Psi(\text{gene}))}, \tag{8}$$

that is, the greater the fitness, the higher the probability of being selected, and the new individuals selected are inserted into the new population Q'.

⑥ The probability P_c is used to randomly select n_2 individuals from the population Q, which is even and convenient for crossover operation. The crossover operation is carried out by randomly extracting a number of individual gene fragments and pairing individuals to form a new individual to join the population Q'. In the optimization process

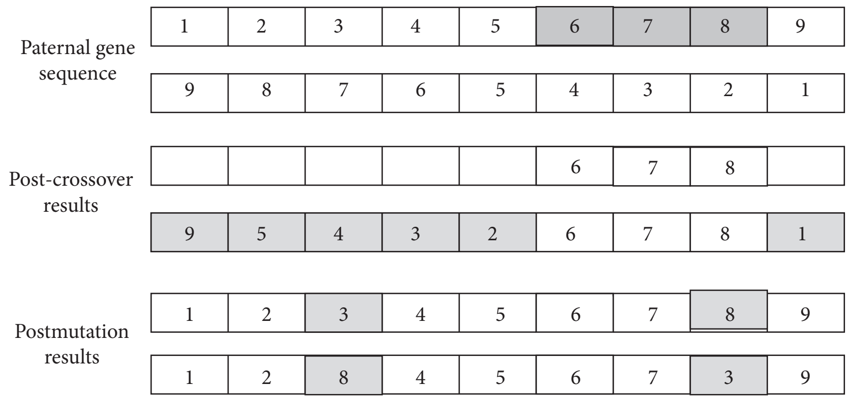

Figure 2: Gene crossover and mutation.

of operation and maintenance of PV plants, P_c is set to 0.75.

In the new population Q', the probability P_m is used to randomly select n_3 individuals, which is for mutation. That is to say, two gene fragments are randomly selected, and their positions are exchanged to form n_3 new individuals to join the population Q'. In the optimization process of operation and maintenance of PV plants, P_m is set to 0.01. The crossover method and the mutation method are shown in Figure 2.

Two individuals were selected randomly with probability P_c to perform crossover operation. The offspring inherited part of the genes from their parents and kept the same sequence as their parents are as shown in Figure 2. Some genes of Parent 1, such as 678, crossed with Parent 2 were selected randomly, and the crossover results are shown in Figure 2.

The probability P_m of mutation occurs. Because each city only passes through once in TSP problem, the mutation should not change the value of one position in the gene sequence (which will cause a city to pass through twice) but should exchange the values of two positions randomly, as shown in Figure 2; the positions of 3 and 8 should be exchanged.

⑦ Repeat ⑤ and ⑥ until the maximum number of iterations is reached, or the fitness function of an individual reaches a given threshold.

⑧ For the individual with the largest output fitness, the sequence of flow numbers is the maintenance sequence given by the algorithm.

Step 3. The optimal operation and maintenance scheme is output by the path optimization algorithm.

Step 4. If when the maintainers implement the optimal path, the operation and maintenance time consuming does not match the expected time consuming or new faults occur during the operation and maintenance period; we need to update the information to solve the fault and repeat Steps 2–4 again, until the maintainers successfully implement the optimal path.

4. Experiments and Implementation Verification

The experimental environment uses MATLAB 6.0 to construct 36 random points as the distribution of PV plants in the region and triangulate the points, and the time spent on the road is the sum of the edge lengths of the triangle experienced between the two points; construct the weight matrix of the operation and maintenance process, randomly select a number of points from the points as maintenance objects, and set them up again every 1 minute from the points. Randomly select 0 to 1 point as a new maintenance object to join the maintenance queue. Suppose a maintainer is at a fixed speed between the set of points in the operation and maintenance, and the speed per minute does not exceed the length of the maximum edge of the triangle. As shown in Figure 3, randomly generate points, triangulate points, and construct maintenance site.

In the experiment, the maintenance of PV plants can be well carried out by implementing one maintainer and three maintainers, respectively. By implementing a genetic algorithm, the optimal dispatching path of maintainers can be saved, especially when facing 38 photovoltaic power stations, no more than three maintainers can be maintained.

In order to better prove the rationality of the optimization method of operation and maintenance dispatch of PV plants based on genetic algorithm, random method, greedy algorithm, and genetic algorithm were used to carry out experiments. The time consuming on the road between two places of a company's PV plants in Zhejiang province is shown in Table 1, including Hangzhou, Deqing, Haining, Huzhou, Jiande, Kaihua, Kecheng, Linan, Linhai, Longquan, Pan'an, Quzhou, Shangyu, Shaoxing, Shengzhou, Taizhou, Tiantai, Tonglu, Tongxiang, Yuyao, and Zhuji. The PV plants in all areas are repaired and maintained once to find an appropriate operation and maintenance path. The average travel time for each region is 159 minutes, of which

(1) The average total time of 21 horizons patrol by the random route method is 3340 minutes.

(2) Using a greedy algorithm (the next destination is the nearest location from the current location), the route is selected as follows:

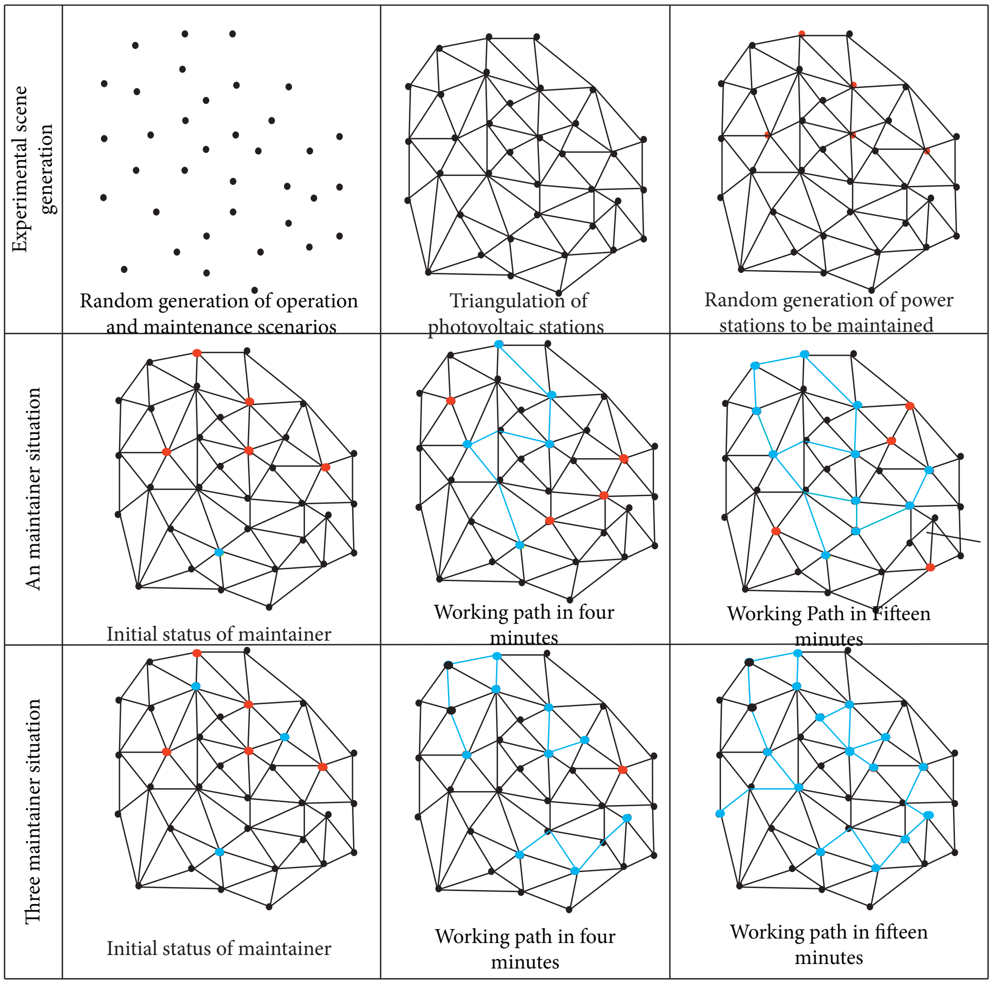

Figure 3: Scenario construction and operation and maintenance path optimization.

Hangzhou > Tongxiang > Haining > Shangyu > Shaoxing > Yuyao > Shengzhou > Tiantai > Linhai > Taizhou > Pan'an > Zhuji > Linan > Deqing > Huzhou > Tonglu > Jiande > Kecheng > Quzhou > Kaihua > Longquan > Hangzhou.

The time series is {61, 35, 65, 45, 40, 86, 69, 54, 68, 144, 99, 98, 73, 58, 140, 66, 71, 13, 61, 217, 313}, totaling 1876 minutes.

(3) The genetic algorithm is used to optimize the maintenance path. The time cost matrix of operation and maintenance location is shown in Table 1. The selected route is as follows:

Hangzhou > Linan > Deqing > Huzhou > Tongxiang > Haining > Zhuji > Shaoxing > Yuyao > Shangyu > Shengzhou > Tiantai > Taizhou > Linhai > Pan'an > Longquan > Kaihua > Kecheng > Quzhou > Jiande > Tonglu > Hangzhou.

The time series is {62, 73, 58, 87, 35, 103, 77, 40, 55, 67, 69, 90, 68, 97, 187, 217, 56, 13, 76, 66, 78}, totaling 1278 minutes.

Compared with the optimal path obtained by the exhaustive wet method, it is confirmed that the improved genetic algorithm can obtain the optimal path for 21 operation and maintenance routes.

The coding method of the genetic algorithm and the definition of fitness function in [34, 35] were used to solve the operation and maintenance route planning of PV plants. Comparing with this algorithm, as shown in Figure 4, [35] needs 81 iterations, [34] needs 44 iterations, while this algorithm only needs 34 iterations, and the final operation and maintenance path takes 1278 minutes. By defining an appropriate fitness function, the strategy of a genetic algorithm to optimize the operation and maintenance path presented in this paper can accelerate the convergence speed and searchability of the genetic algorithm.

5. Summary

This paper presents an optimization method of operation and maintenance dispatch of PV plants based on the genetic algorithm. This method aims at the operation and maintenance tasks of large-scale distributed PV plants. GA

Table 1: Time cost matrix of operation and maintenance sites (unit: minutes).

		0 Hangzhou	1 Deqing	2 Haining	3 Huzhou	4 Jiande	5 Kaihua	6 Kecheng	7 Linan	8 Linhai	9 Longquan	10 Pan'an	11 Quzhou	12 Shangyu	13 Shaoxing	14 Shengzhou	15 Taizhou	16 Tiantai	17 Tonglu	18 Tongxiang	19 Yuyao	20 Zhuji
0	Hangzhou	0	68	67	96	114	198	166	62	189	313	154	170	71	70	104	221	144	78	61	88	82
1	Deqing	68	0	83	58	143	226	194	73	216	339	176	209	101	100	132	248	170	110	92	115	110
2	Haining	67	83	0	98	154	238	204	114	176	313	162	209	65	83	94	210	132	119	35	79	103
3	Huzhou	96	58	98	0	175	265	230	119	245	370	206	237	131	132	160	283	200	140	87	146	139
4	Jiande	114	143	154	175	0	102	71	125	219	210	170	76	149	139	177	258	213	66	169	165	136
5	Kaihua	198	226	238	265	102	0	56	197	241	217	191	61	227	216	199	281	235	135	250	254	166
6	Kecheng	166	194	204	230	71	56	0	182	197	189	150	13	188	177	156	236	194	100	214	207	127
7	Linan	62	73	114	119	125	197	182	0	244	315	167	176	129	105	164	281	200	89	104	144	98
8	Linhai	189	216	176	245	219	241	197	244	0	228	97	208	148	167	112	68	54	261	205	151	172
9	Longquan	313	339	313	370	210	217	189	315	228	0	187	192	280	281	241	276	267	247	331	313	255
10	Pan'an	154	176	162	206	170	191	150	167	97	187	0	164	132	127	88	144	88	171	175	156	99
11	Quzhou	170	209	209	237	76	61	13	176	208	192	164	0	195	187	173	248	210	108	226	213	136
12	Shangyu	71	101	65	131	149	227	188	129	148	280	132	195	0	45	67	186	117	120	99	55	87
13	Shaoxing	70	100	83	132	139	216	177	105	167	281	127	187	45	0	68	187	109	120	99	40	77
14	Shengzhou	104	132	94	160	177	199	156	164	112	241	88	173	67	68	0	153	69	154	117	86	107
15	Taizhou	221	248	210	283	258	281	236	281	68	276	144	248	186	187	153	0	90	273	234	179	212
16	Tiantai	144	170	132	200	213	235	194	200	54	267	88	210	117	109	69	90	0	191	161	127	144
17	Tonglu	78	110	119	140	66	135	100	89	261	247	171	108	120	120	154	273	191	0	121	136	107
18	Tongxiang	61	92	35	87	169	250	214	104	205	331	175	226	99	99	117	234	161	121	0	101	105
19	Yuyao	88	115	79	146	165	254	207	144	151	313	156	213	55	40	86	179	127	136	101	0	97
20	Zhuji	82	110	103	139	136	166	127	98	172	255	99	136	87	77	107	212	144	107	105	97	0

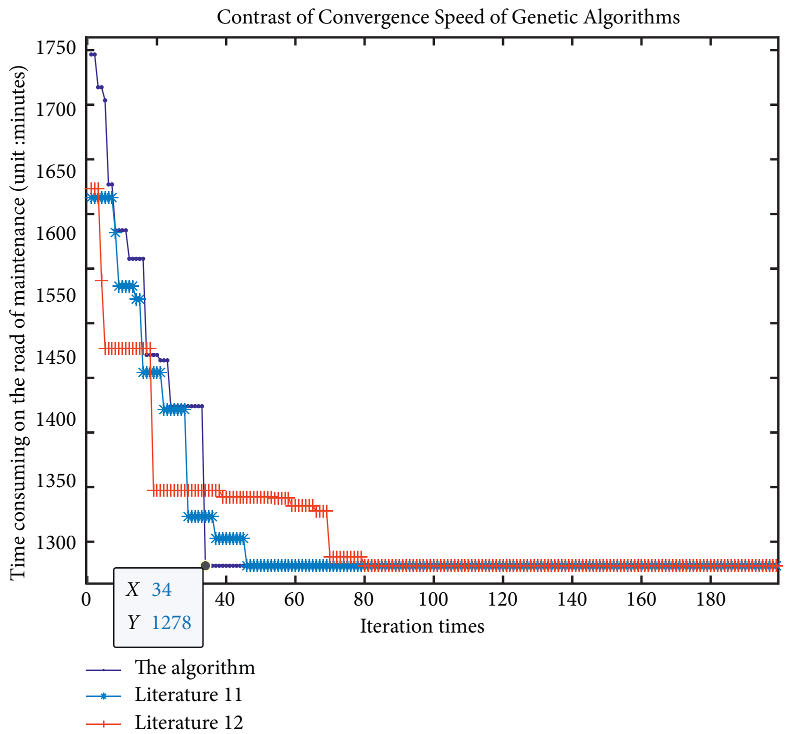

Figure 4: Comparison of convergence speed of genetic algorithms.

for M-TSP is applied to provide an optimal path for maintainers dispatched for PV plants. It supports the optimization of operation and maintenance dispatch of multiple PV plants, multimaintainer, multiobjective, and multipoint departure. By multitype cost function, different assignment constraints or cost considerations can be set, such as arrival within a specified time or minimum time cost of transportation costs. We ascertain that the proposed model will lead the way.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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