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Application of Optimization Algorithms for Optimal Inspection Path Planning in Multi-point Distribution Stations

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Generally, medium and large electromechanical maintenance vendors have more than one distribution station. These require routine inspections and maintenance to continue the normal operations of distribution station equipment. Therefore, in this study, we divided routine maintenance time into annual, seasonal, and monthly cycles to develop the optimal inspection route and reduce maintenance costs. We selected 31 universities in Taiwan as the distribution station locations for testing. We used Google My Maps to establish each university's geographical location and to query the traffic time and distance between each university. Finally, maintenance and traffic times were incorporated into the working time and inputted into a particle swarm optimization. The working time and distance traveled were calculated to optimize the inspection route. The test results indicate that the particle swarm optimization performed better than the genetic algorithm for inspection route optimization. The computer execution time of applying the particle swarm optimization was 0.85 s when performing multi-point inspection optimal route planning for the 31 distribution stations. Therefore, particle swarm optimization could significantly reduce route planning time and inspection costs while achieving smart route optimization goals.

1. Introduction

Electromechanical vendors must regularly conduct equipment inspections to ensure normal operation and promptly detect and solve potential issues. However, planning inspection routes requires significant time and human resources, particularly when large-scale equipment is involved. Therefore, optimizing inspection routes can help electromechanical vendors reduce time and costs while improving inspection efficiency and accuracy.

In this study, the Google My Maps application was utilized, and the GPS sensor system developed by Google itself was used to extract traffic information and route navigation between distribution stations. Launched in 2007, My Maps helps people create their own custom maps on

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top of Google Maps.(1) The integration of GPS and compass enables the precise location tracking of maintenance personnel, making navigation anywhere in the world easier.(2) Žunić *et al*. used GPS data to track vehicles, analyze their routes, and improve the performance of vehicle routing algorithms.(3) The results indicated that improving the input data for the algorithms can lead to better estimation of when vehicles will arrive at customer locations and their duration of stay, ultimately reducing the number of unsuccessful customer visits.(3)

The traveling salesman problem (TSP) is a classic combinatorial optimization problem and a typical example of a nondeterministic polynomial (NP) problem.(4,5) The basic principle of the typical TSP is that a salesperson visits *n* cities, starting from a particular initial city, passing through all cities in sequence, and finally returning to the initial city. Each city must be visited once and only once. The objective is to determine the shortest path that satisfies these conditions. The TSP is often solved using various optimization algorithms, such as the genetic algorithm (GA),(6) particle swarm optimization (PSO),(7,8) simulated annealing,(9) ant colony optimization,(10,11) and the artificial bee colony.(12) Chen *et al*. applied a chaotic neural network and GA to path planning.(13) The planning result was obtained from the chaotic neural network and then encoded into chromosomes, which replaced the worst individual in the GA population. After the algorithm, a new path was obtained. The results showed that this method can be used for robot inspections in remote wind farms. Gong *et al*. transformed the automatic sampling process in unmanned sailboat inspections into a TSP.(14) They proposed an improved PSO to address the premature convergence issue associated with the traditional PSO. They introduced crossover and mutation operations from the GA during the optimization process. The results indicate that the PSO was simple to implement and had a fast convergence speed.(14) In this study, we aimed to optimize inspection routes. The concept is similar to that of the TSP. Therefore, we refer to the TSP and use the PSO to solve the optimization of inspection routes.

2. Developing an Optimal Inspection Route Platform for Distribution Stations

Maintenance and operation companies conduct routine maintenance on multiple distribution station equipment and require the preplanning of optimal inspection routes for maintenance personnel. This is conducted to achieve maximum efficiency within a given time frame, reduce transportation time, lower maintenance costs, and improve management efficiency. In this study, we divided routine maintenance into three periods: annual, quarterly, and monthly. Additionally, we selected 31 universities in Taiwan as simulation testing locations for distribution stations. Using Google My Maps, we established the geographic areas of the 31 universities and simulated maintenance routes. The geographic locations of the selected universities are shown in Fig. 1.

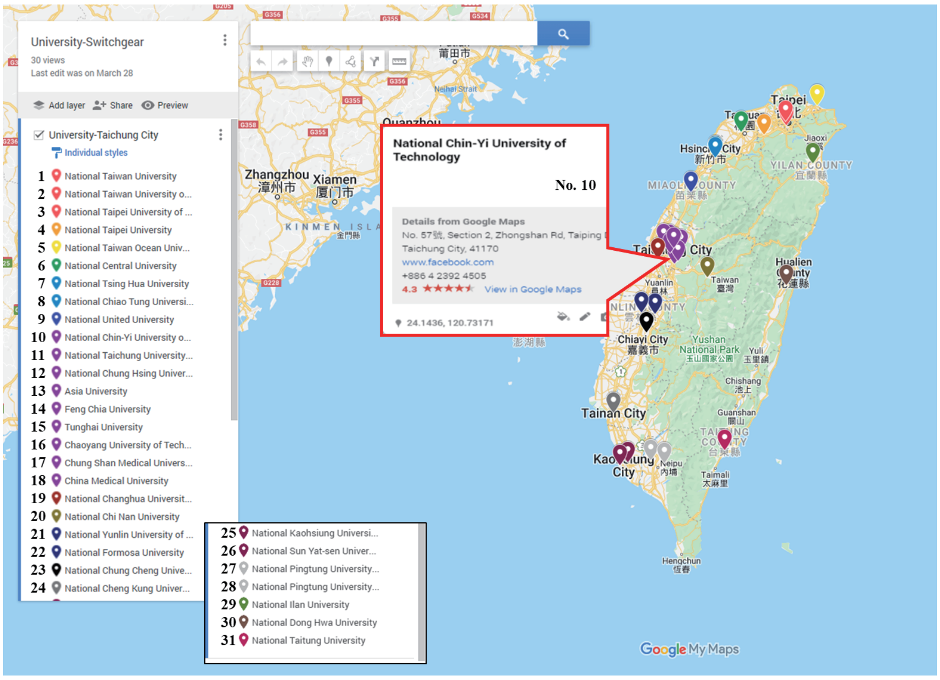


Fig. 1. (Color online) Geographical locations of each distribution station and No. 10 established in this study.

3. Parameter Settings for Inspection Route Optimization

3.1 Working time setting for inspection routes

Traditionally, maintenance personnel rely on their past experience and knowledge of traffic conditions to estimate maintenance and transportation times. This approach is not always accurate and can be challenging for new maintenance personnel, leading to reduced work efficiency. Therefore, in this study, we focused on optimizing smart inspection routes. On the basis of the data on the area, size, and number of students in each university or college provided by the Ministry of Education for the academic year 2020–2021, we established a customized scale of maintenance time intervals for each university or college. We then used the maintenance time interval scale to classify the scale of each distribution station at 31 universities and colleges. A representation of the maintenance time interval scale and its application to some of the distribution stations are shown in Table 1.

3.1.1 Maintenance time

First, the Google My Maps locations of 31 universities in Taiwan were established. The traffic times and distances between the universities were obtained to create a path matrix. Additionally, the traffic times were classified into peak and off-peak hours. We defined the scale ranking on the basis of the campus size, the student population, and the level of urban development in the surrounding area. Maintenance times were then self-defined and are presented in Table 2, including annual, quarterly, and monthly maintenance periods.

Table 1
A portion of the 31 universities was selected to demonstrate the distribution station scale.

Number	Campus area (m^2)	Number of students	Campus scale category
1	1368343	32527	1
2	346431	11171	2
3	147823	13837	3
4	590862	10080	3
5	338412	8905	3
6	639193	11938	2
7	1222740	16917	1
8	878888	15182	1
9	769619	7559	3
10	327477	12134	3

Table 2
Setting maintenance time according to campus scale category.

Campus scale category	Yearly maintenance time (min)	Quarterly maintenance time (min)	Monthly maintenance time (min)
1	150	120	90
2	120	90	60
3	90	60	30
4	60	30	15

3.1.2 Traffic time

In this study, we used Google My Maps to search for traffic data between distribution stations. The traffic time and distance between distribution stations were established on the basis of the data obtained. Peak and off-peak traffic times could also be obtained by selecting the departure time on Google My Maps. Figure 2 shows that departing at 8 a.m. from No. 10 to No. 16, the route recommended by Google My Maps, was used as a template to establish the off-peak and peak traffic times of 24–45 min with a distance of 12 km between No. 10 and No. 16. Similarly, the traffic data between Nos. 10 and 16 was also established. By this method, the traffic data between the 31 distribution stations were established in a 31 × 31 matrix and are shown in Tables 3–5.

The maintenance and traffic times were incorporated into the daily working time. The working time was inputted into the PSO. After calculation, the optimal route working time and travel distance were obtained. With these two data, the economic benefits and costs this technology were evaluated to achieve the concept and function of smart inspection.

3.2 Cost setting of patrol route

Using the TSP combined with the PSO, we developed a system for optimizing inspection routes. First, maintenance personnel can freely select the initial maintenance position and the time for that position. Next, under the constraint that the daily working time must not exceed 8 h, the maintenance personnel obtained the traffic distance and travel time between the maintenance location and other nearby locations requiring maintenance. Furthermore, the total working time

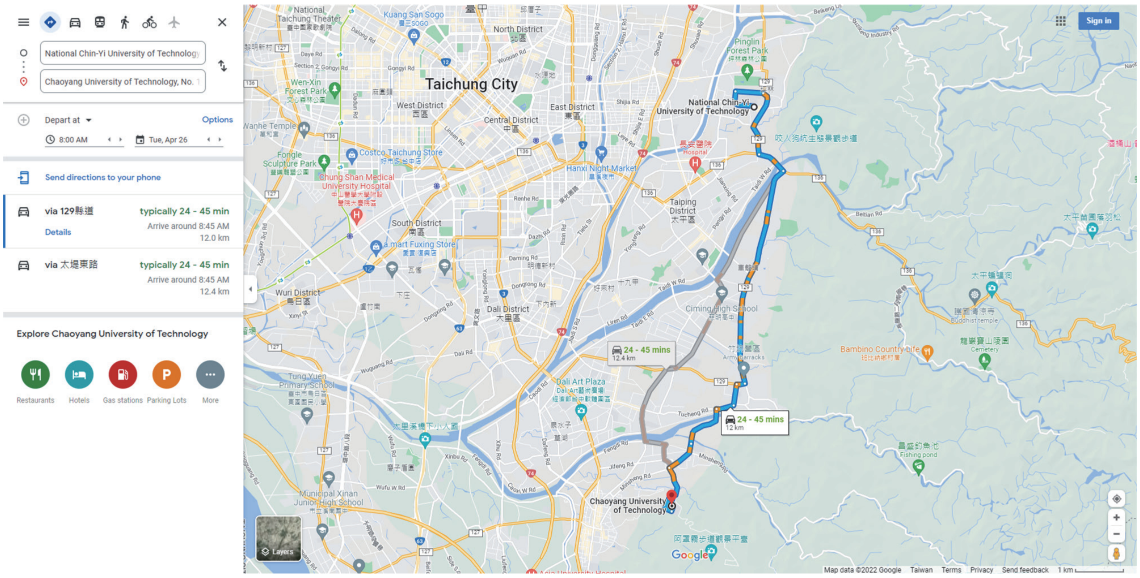


Fig. 2. (Color online) Google My Maps route navigation.

Table 3
Setting traffic time for local distribution stations based on peak times.

Peak (min)	No. 10	No. 11	No. 12	No. 13
No. 10	0	35	35	40
No. 11	30	0	22	45
No. 12	40	28	0	28
No. 13	35	40	26	0

Table 4
Setting traffic time for local distribution stations based on off-peak times.

Off-peak (min)	No. 10	No. 11	No. 12	No. 13
No. 10	0	22	26	26
No. 11	22	0	26	27
No. 12	26	26	0	17
No. 13	26	27	17	0

Table 5
Traffic distance between local distribution stations.

Traffic distance (km)	No. 10	No. 11	No. 12	No. 13
No. 10	0	6	8.1	18.2
No. 11	6.1	0	4	15.9
No. 12	8.3	4.9	0	12.7
No. 13	17.5	17	12.6	0

was calculated by summing the maintenance and traffic times for each point without considering the optimized path. The final maintenance path was obtained through the PSO, which predicted the optimized path for one workday within the legal limit of 8 h. However, if it is necessary to extend the working hours owing to work requirements, the total duration should not exceed 12 h. In this study, we considered working time and traffic distance as sources for calculating the economic cost. If the working time exceeded 8 h, it was calculated as overtime pay.(15) The traffic distance was calculated on the basis of the average fuel consumption of 10 km per liter of gasoline. Additionally, the cost per km for the vehicle and the carbon emission per liter of gasoline were also calculated on the basis of the traffic distance.

According to the Petroleum Price Information Management and Analysis System of the Bureau of Energy, Ministry of Economic Affairs,(16) the weekly average prices of gasoline and diesel for the period from March 05, 2023 to March 11, 2023 were as follows: Unleaded 98 was priced at 32.38 NTD per liter (approximately 1.079 USD using an exchange rate of 1 USD to 30 NTD); Unleaded 95 was priced at 30.37 NTD per liter (approximately 1.012 USD); Unleaded 92 was priced at 28.87 NTD per liter (approximately 0.962 USD); Super Diesel was priced at 27.03 NTD per liter (approximately 0.901 USD), as shown in Fig. 3.

In this study, we set the parameters for the economic cost of path optimization, as shown in Table 6. We assumed that two maintenance personnel were on a business trip, who were both paid a monthly salary of approximately 1350 USD under the monthly salary system. The fuel consumption for driving a vehicle was 10 km per liter, and the price of Unleaded 95 gasoline was 30.37 NTD per liter (approximately 1.012 USD). The overtime pay and fuel costs can be calculated using Eqs. (1) to (3). Additionally, assuming a vehicle price of approximately 27000 USD, an annual cost of insurance and maintenance of 1700 USD, and a total mileage of 300000 km, the vehicle's cost per km can be calculated using Eq. (4). According to the Green Vehicle Guide from the Environmental Protection Administration, the recommended CO_2 emission factor for gasoline used in vehicles is 2.2631 $kgCO_2/L$, which was used to calculate the carbon emission per liter of gasoline in this study.(17)

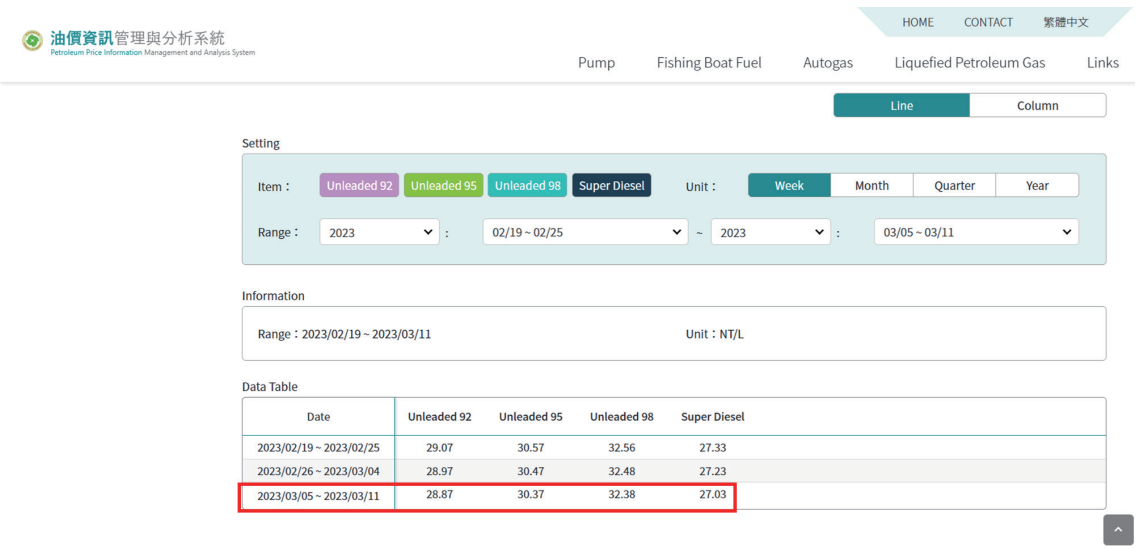


Fig. 3. (Color online) Retail pump prices according to Petroleum Price Information Management and Analysis System.

Table 6
Traffic distance between local distribution stations.

Parameter	Unit of quantity
Number of maintenance personnel	2
Salary of maintenance personnel 1	1350 USD/monthly
Salary of maintenance personnel 2	1350 USD/monthly
Mileage per liter	10 km/liter
Price for Unleaded 95 gasoline (2023/03/05–03/11)	1.012 USD/liter
Cost per km of vehicle	0.175 USD/lm
Carbon emission per liter of gasoline	2.2631 $kgCO_2$/liter

$$Overtime\ pay = \frac{Monthly\ salary}{30 \times 8} \times \frac{4}{3} \times \left(Overtime\ hours - 8\right) \tag{1}$$

$$Overtime\ pay = \frac{Monthly\ salary}{30 \times 8} \times \frac{4}{3} \times 2 + \frac{Monthly\ salary}{30 \times 8} \times \frac{5}{3} \times \left(Overtime\ hours - 8\right) \tag{2}$$

$$Fuel\ cost = \frac{Traffic\ distance}{Mileage\ per\ liter} \times Cost\ of\ gasoline\ per\ liter \tag{3}$$

$$Cost\ per\ km\ of\ vehicle = \frac{Vehicle\ price + Maintenance\ and\ insurance\ cost \times lifespan}{Total\ mileage\left(\mathrm{km}\right)} \tag{4}$$

Owing to the consideration that the working hours may be less than 8 h, there is no need to calculate overtime pay. Therefore, we differentiate the working time using overtime hour. If the overtime hours were within 2 h, they were calculated using Eq. (1). If the overtime hours were extended for another 2 h, they were calculated using Eq. (2). The difference between the overtime hours and 8 regular hours was calculated in 0.5 h increments.

4. Methodology

The TSP is a classic combinatorial optimization problem and a typical example of an NP problem.[18–20] The classic TSP's basic principle is that a traveling salesperson needs to visit n cities. The salesman departs from a certain initial city, sequentially visits all cities, and finally returns to the initial city. Each city must be visited once and only once under this condition. The shortest path of the visiting route is sought.

Maintenance personnel depart from a maintenance center or a substation and proceed to a site for routine equipment maintenance. There may be more than one maintenance location, and after completing the maintenance of all equipment at the maintenance locations, they return to the starting point. In this study, we inputted the working time into the PSO. The optimized path concerning working time and traffic distance was obtained through computation. The economic cost was evaluated on the basis of the working time and traffic distance using the parameter settings presented in Table 6. We also inputted the working time into the GA to obtain the optimized path concerning working time and traffic distance. The results were compared with those of the PSO. The design process for optimizing the patrol path is shown in Fig. 4.

4.1 Particle swarm optimization

Kennedy and Eberhart proposed PSO as a universal heuristic algorithm in 1995. (21,22) It has since been widely used to solve combinatorial optimization problems. PSO is inspired by the foraging behavior of fish or birds simulated as an algorithm. Through the interaction between individuals, a group's collective behavior is generated to achieve optimization objectives.

Initially, particles are randomly placed in the search space, with each particle containing its position and velocity. The fitness value of each particle is then calculated. Each particle uses its individual best solution (*pbest*) and the global best solution (*gbest*) to update its movement direction and distance, adjusting its current position and determining whether the current best solution is improved on the basis of the fitness value. This process is iterated until global optimization is achieved. The velocity and position of each particle are updated using Eqs.(5) and (6) in each iteration.

$$V_i(n+1) = w \times V_i(n) + c_1 \times rand \times \left(p_i(n) - x_i(n)\right) + c_2 \times rand \times \left(g(n) - x_i(n)\right) \tag{5}$$

$$x_i(n+1) = x_i(n) + V_i(n+1) \tag{6}$$

Here, V_i represents the velocity of each particle, i is the particle index, n is the number of iterations, w is the inertia weight, c_1 and c_2 are the cognitive and social learning coefficients, respectively, $rand$ is a random variable between 0 and 1, p_i is the personal best position of each particle, g is the global best position of the swarm, and x_i is the current position of each particle.

4.2 Genetic algorithm

The GA is a type of heuristic algorithm inspired by the concept of "survival of the fittest", as described by Charles Darwin in his 1859 book "On the origin of species". The primary purpose

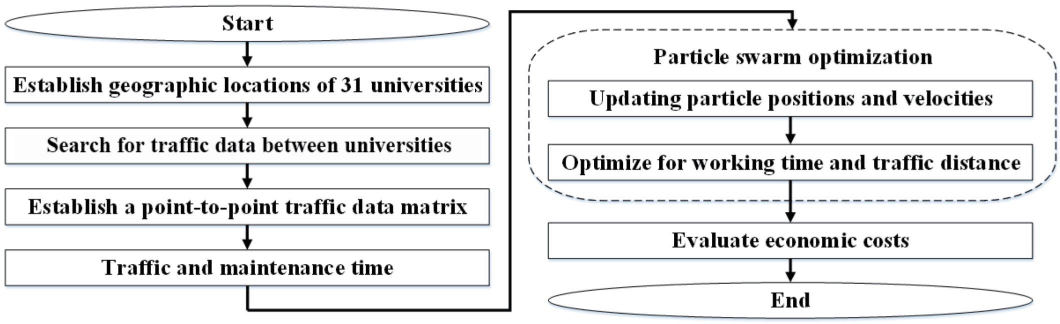


Fig. 4. Inspection route optimization flow chart.

of the GA is to solve optimization problems. John Holland's book "Adaptation in Natural and Artificial Systems", published in 1975, is considered the founding work on GA. J. Holland is also known as the father of GA. His book proposes simulating genetic operations with leading operators such as selection, crossover, and mutation. The GA concept involves an individual composed of genes and a population composed of individuals. Genes are the basic units that comprise chromosomes. Therefore, individuals are also known as chromosomes. For both the fitness functions of PSO and GA, the independent variables are the traffic times between stations, whereas the dependent variable is the optimal traffic time of the inspection route.

5. Experimental Results

When a maintenance company for electromechanical equipment conducts regular inspections on power equipment at multiple substations, it is essential to plan the optimal route and task execution in advance to ensure adequate maintenance and machine calibration. This can help reduce the risk of equipment abnormalities and operating costs while improving management efficiency and digital data management. Therefore, in this study, we took the initial distribution station location specified by the maintenance company's operators and automatically generated nearby locations requiring maintenance. The traffic information matrix of this multi-point distribution station was then inputted into the PSO and GA for path optimization calculation. It was then divided into peak and off-peak traffic times. Each substation's maintenance schedule was set to yearly, quarterly, monthly, and a mixed maintenance period to observe the difference between the PSO and the GA. In the manual selection of stations, the maintenance schedule for each substation was set to a random maintenance period to compare the performance of both algorithms, given that the flexibility in selecting maintenance time and substations was higher. Furthermore, the time taken for each optimal path in each scenario was used to calculate the daily wage payment, overtime pay, fuel cost, vehicle cost per km, and carbon emission per liter of gasoline, according to Eqs. (1) and (2) using the parameters in Table 6.

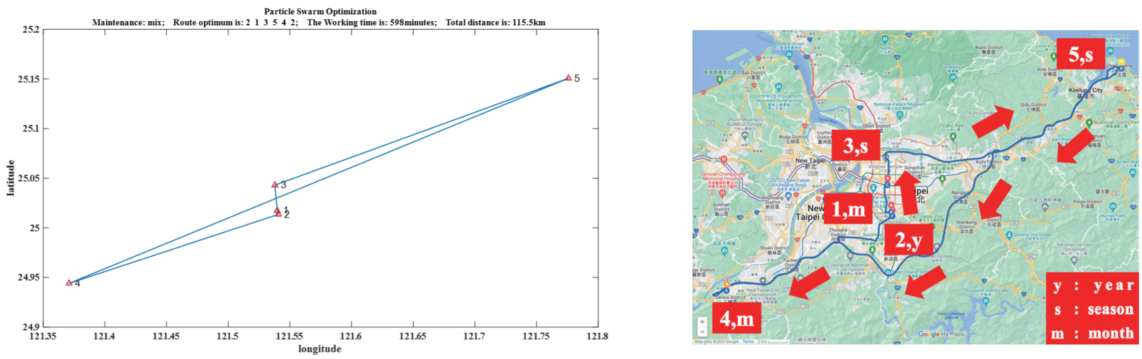
5.1 Optimized path results using PSO

5.1.1 Traffic time during peak times

In the scenario with peak traffic, the optimized path for the fourth scenario was 2→1→3→5→4→2, with a maintenance cycle of yearly, monthly, quarterly, monthly, and quarterly. The working time was 9.9667 h and the traffic distance was 115.5 km. According to Eqs. (1)–(4) and Table 7, the overtime pay was 15 USD per person, the fuel cost was 11.69 USD, the cost per km was 20.21 USD, and the carbon dioxide emission per liter of gasoline was 26.14 $kgCO_2$. The total cost for that day was 152 USD. The optimized path and navigation for this scenario are shown in Fig. 5. The results for all four scenarios are summarized in Table 7.

Table 7
Results of PSO for route optimization in peak times.

Scenarios	Results of PSO for route optimization (peak)			
1	No. 10 → No. 14 → No. 18 → No. 11 → No. 10			
2	No. 24 → No. 26 → No. 25 → No. 24			
3	No. 7 → No. 8 → No. 14 → No. 9 → No. 7			
4	No. 2 (yearly) → No. 1 (monthly) → No. 3 (quarterly) → No. 5 (monthly) → No. 4 (quarterly) → No. 2			
Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Working time	8.85 h	9.5 h	7.65 h	9.9667 h
Traffic time	29.9 km	112.7 km	183.6 km	115.5 km
Overtime pay	8 USD/person	11 USD/person	0 USD/person	15 USD/person
Fuel cost	3.03 USD	11.41 USD	18.58 USD	11.69 USD
Vehicle cost	5.23 USD/km	19.72 USD/km	32.13 USD/km	20.21 USD/km
Carbon emission	6.7667 $kgCO_2/L$	25.5051 $kgCO_2/L$	41.5505 $kgCO_2/L$	26.1388 $kgCO_2/L$
Total daily	114 USD	143 USD	141 USD	152 USD



(a) (b)

Fig. 5. (Color online) PSO for path optimization with randomized maintenance schedule during peak: (a) schematic diagram of path optimization; (b) navigation for optimized path.

5.1.2 Traffic time during off-peak times

The optimal route for Scenario 4 during off-peak was 2→1→3→6→4→2, with a maintenance schedule of quarterly, monthly, quarterly, monthly, and yearly. The working time was 8.28 h, and the traffic distance was 101.8 km. The overtime pay was 4 USD per person, the fuel cost was 10.30 USD, the cost of vehicle maintenance per km was 17.82 USD, and the carbon emission per liter of gasoline was 23.0384 $kgCO_2$. The total cost for the day was 126 USD. The results for all four scenarios are summarized in Table 8.

5.2 Optimized path results using GA

5.2.1 Traffic time during peak times

The optimal route for Scenario 4 during peak was 2→1→5→3→4→2, with a maintenance cycle of yearly, monthly, monthly, quarterly, and quarterly. The working time was 10.55 h and

Table 8
Results of PSO for route optimization in off-peak times.

Scenarios	Results of PSO for route optimization (off-peak)			
1	No. 10 → No. 11 → No. 18 → No. 12 → No. 10			
2	No. 24 → No. 25 → No. 26 → No. 24			
3	No. 7 → No. 8 → No. 6 → No. 3 → No. 1 → No. 7			
4	No. 2 (quarterly) → No. 1 (monthly) → No. 3 (quarterly) → No. 6 (monthly) → No. 4 (yearly) → No. 2			
Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Working time	8.63 h	8 h	8.3667 h	8.28 h
Traffic time	21.5 km	112.5 km	167.1 km	101.8 km
Overtime pay	8 USD/person	0 USD/person	4 USD/person	4 USD/person
Fuel cost	2.18 USD	11.39 USD	16.91 USD	10.30 USD
Vehicle cost	3.76 USD/km	19.69 USD/km	29.82 USD/km	17.82 USD/km
Carbon emission	4.8657 $kgCO_2/L$	25.4599 $kgCO_2/L$	37.8164 $kgCO_2/L$	23.0384 $kgCO_2/L$
Total daily	112 USD	121 USD	144 USD	126 USD

the traffic distance was 121.4 km. The overtime pay was 23 USD per person, the fuel cost was 12.29 USD, the cost per km of vehicle usage was 21.25 USD, and the carbon dioxide emission per liter of gasoline was 27.4740 $kgCO_2$. The total cost for the day was 170 USD. The optimized route and navigation for this scenario are shown in Fig. 6. The results for all four scenarios are summarized in Table 9.

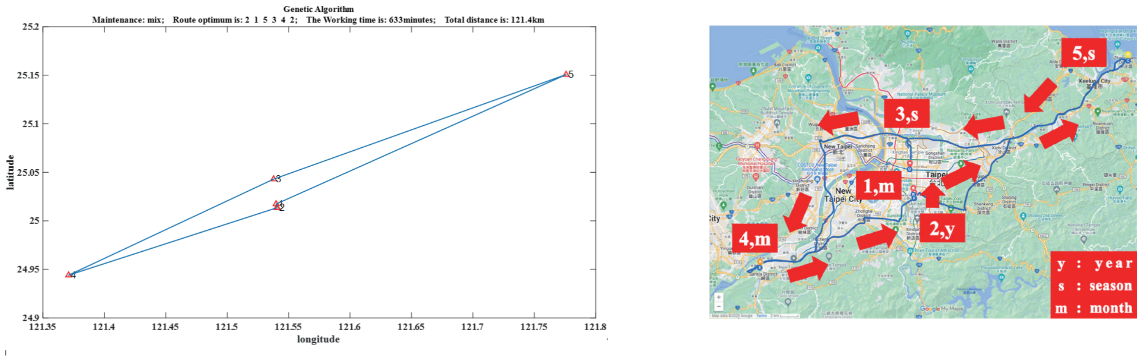
5.2.2 Traffic time during off-peak times

The optimal route for Scenario 4 during off-peak was 2→4→6→3→1→2, with a maintenance cycle of quarterly, yearly, monthly, quarterly, and monthly, and the working time was 8.3167 h. The traffic distance was 106 km and the overtime pay was 4 USD per person. The fuel cost was 10.73 USD and the vehicle cost per km was 18.55 USD. The carbon emission per liter of gasoline was 23.9889 $kgCO_2$ and the total cost for the day was 127 USD. The results for the four scenarios are summarized in Table 10.

Tables 7–10 indicate that regardless of peak or off-peak traffic conditions, the PSO performs better than the GA in optimizing the inspection route. The performance comparison between the two methods in terms of working hours, travel distance, vehicle cost per km, and gasoline carbon emission during peak traffic hours is summarized in Table 11.

5.3 Results of manually selected route optimization

We also compared the route optimization results using the PSO and GA by inputting all 31 distribution stations. Starting from No.10, the distribution stations were divided into four regions for maintenance: central, northern, eastern, and southern. The route then returned to the central region before returning to No.10. The total working time for this round-island maintenance was one month, and the maintenance period was annual. Owing to the high uncertainty of daily working hours under these conditions, the human resource costs such as overtime pay were not



(a) (b)

Fig. 6. (Color online) GA for path optimization with randomized maintenance schedule during peak: (a) schematic diagram of path optimization; (b) navigation for optimized path.

Table 9
Results of GA for route optimization in peak times.

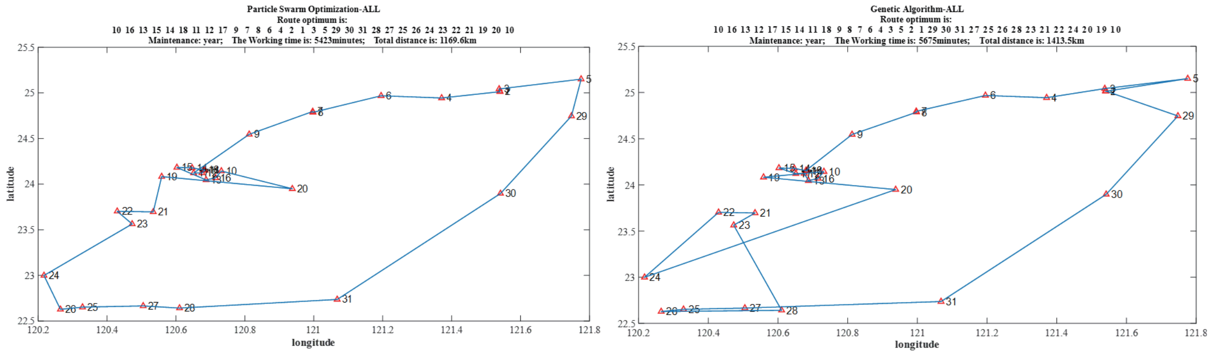
Scenarios	Results of GA for route optimization (peak)			
1	No. 10 → No. 11 → No. 18 → No. 12 → No. 10			
2	No. 24 → No. 25 → No. 26 → No. 24			
3	No. 7 → No. 8 → No. 6 → No. 3 → No. 1 → No. 7			
4	No. 2 (quarterly) → No. 1 (monthly) → No. 3 (quarterly) → No. 6 (monthly) → No. 4 (yearly) → No. 2			
Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Working time	8.63 h	8 h	8.3667 h	8.28 h
Traffic time	21.5 km	112.5 km	167.1 km	101.8 km
Overtime pay	8 USD/person	0 USD/person	4 USD/person	4 USD/person
Fuel cost	2.18 USD	11.39 USD	16.91 USD	10.30 USD
Vehicle cost	3.76 USD/km	19.69 USD/km	29.82 USD/km	17.82 USD/km
Carbon emission	4.8657 $kgCO_2/L$	25.4599 $kgCO_2/L$	37.8164 $kgCO_2/L$	23.0384 $kgCO_2/L$
Total daily	112 USD	121 USD	144 USD	126 USD

Table 10
Results of GA for route optimization in off-peak times.

Scenarios	Results of GA for route optimization (off-peak)			
1	No. 10 → No. 18 → No. 11 → No. 12 → No. 10			
2	No. 24 → No. 26 → No. 25 →→ No. 24			
3	No. 7 → No. 8 → No. 1 → No. 3 → No. 6 → No. 7			
4	No. 2 (quarterly) → No. 4 (yearly) → No. 6 (monthly) → No. 3 (quarterly) → No. 1 (monthly) → No. 2			
Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Working time	8.8667 h	8 h	8.38 h	8.3167 h
Traffic time	21.2 km	112.7 km	169 km	106 km
Overtime pay	8 USD/person	0 USD/person	4 USD/person	4 USD/person
Fuel cost	2.15 USD	11.41 USD	17.10 USD	10.73 USD
Vehicle cost	3.71 USD/km	19.72 USD/km	29.58 USD/km	18.55 USD/km
Carbon emission	4.7978 $kgCO_2/L$	25.5051 $kgCO_2/L$	38.2464 $kgCO_2/L$	23.9889 $kgCO_2/L$
Total daily	112 USD	121 USD	145 USD	127 USD

Table 11
Performance comparison of two methods during peak traffic hours.

Algorithm performance	PSO	GA
Average working time (h)	8.992	9.178
Average traffic distance (km)	110.425	112.125
Average vehicle cost (USD/km)	19.32	19.62
Average carbon emission ($kgCO_2/L$)	24.99	25.38



(a) (b)

Fig. 7. (Color online) Optimized maintenance route for island-wide power distribution stations: (a) schematic diagram of the maintenance route optimized by PSO; (b) schematic diagram of the maintenance route optimized by GA.

Table 12
Optimized maintenance route for island-wide power distribution stations.

Method 1	PSO
Optimal route path	10→16→13→15→14→18→11→12→17→9→7→8→6→4→2→1→3→5→29→30→31→28→27→25→26→24→23→22→21→19→20→10
Total working time	90.38 h
Total traffic distance	1169.6 km
Total fuel cost	118.36 USD
Total vehicle cost	204.68 USD
Total gasoline emission	264.6922 $kgCO_2/L$
Computer execution time	0.85 s
Method 2	**GA**
Optimal route path	10→16→13→12→17→15→14→11→18→9→8→7→6→4→3→5→2→1→29→30→31→27→25→26→28→23→21→22→24→20→19→10
Total working time	94.583 h
Total traffic distance	1413.5 km
Total fuel cost	143.05 USD
Total vehicle cost	247.36 USD
Total gasoline emission	319.8892 $kgCO_2/L$
Computer execution time	1.39 s

considered. Therefore, the optimal route for round-island maintenance was evaluated on the basis of the economic costs of fuel, vehicle cost per km, and gasoline carbon emission.

Using the PSO, we applied the annual maintenance cycle to a one-month island-wide maintenance period, with a total working time of 5423 min (or 90.38 h) and a total traffic distance of 1169.6 km. The total cost of gasoline for the car was 118.36 USD, the total cost of car consumption per km was 204.68 USD, and the total carbon emission of gasoline per liter was 264.6922 kgCO_2/L. The computer execution time was 0.85 s, and the optimized route is shown in Fig. 7(a). Additionally, by applying the GA to the one-month island-wide annual maintenance cycle, the total working time was 5675 min (94.583 h), the total distance traveled was 1413.5 km, the total cost of car refueling was 143.05 USD, the total cost of car consumption per km was 247.36 USD, and the total carbon emission of gasoline per liter was 319.8892 kgCO_2/L. The computer execution time was 1.39 s, and Fig. 7(b) shows the route optimization diagram. The optimal route information obtained by the two methods is summarized in Table 12 to highlight the differences between the two methods.

6. Conclusions

In this study, we simulated the optimization of inspection routes for power distribution stations, with 31 universities and colleges in Taiwan serving as the locations of these stations. The goal was to maintain the power distribution stations. First, the maintenance starting point was set. The nearby power distribution stations were automatically searched as the required maintenance route schedule through the study design. The maintenance cycle of the maintenance station's machine was selected; its route was inputted into the optimization algorithm to obtain the optimal route's working time and traffic distance. According to the experimental results, the PSO performs better than the GA in optimizing the path. While there is not much difference between the two algorithms in general situations, the cost difference is significant in the long term. The computer execution time of the PSO was 0.85 s. That of the GA was 1.39 s, indicating that the PSO performs faster than the GA in optimizing inspection routes. Using optimization algorithms can also save time in the manual selection of inspection stations. In this study, we also combined inspection routes with Google My Maps navigation and calculated the inspection costs and related carbon footprint, enhancing the ESG indicators of the maintenance and operation company.

Considering the constraint that the daily working time should not exceed 8 h, the number of route points that need to be optimized is limited. As a result, there is relatively little difference when comparing two algorithms. However, if all route points are included in the calculations, total working time, total traffic distance, total fuel cost, total vehicle cost, total gasoline emission and computer execution time have a large difference. In future research, the number of distribution stations requiring route optimization can be gradually increased, and additional optimization algorithms can be introduced for comparison. The objective would be to select the most suitable algorithm while taking into account various economic costs, with the aim of improving the efficiency of maintenance personnel during inspections.

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