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Article

Low Carbon Footprint Routes for Bird Watching

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Abstract: Bird watching is one of many recreational activities popular in ecotourism. Its popularity, therefore, prompts the need for studies on energy conservation. One such environmentally friendly approach toward minimizing bird watching's ecological impact is ensuring a reduced carbon footprint by using an economic travel itinerary comprising a series of connected routes between tourist attractions that minimizes transit time. This study used a travel-route planning approach using geographic information systems to detect the shortest path, thereby solving the problems associated with time-consuming transport. Based on the results of road network analyses, optimal travel-route planning can be determined. These methods include simulated annealing (SA) and genetic algorithms (GA). We applied two algorithms in our simulation research to detect which one is an appropriate algorithm for running carbon-routing algorithms at the regional scale. SA, which is superior to GA, is considered an excellent approach to search for the optimal path to reduce carbon dioxide and high gasoline fees, thereby controlling travel time by using the shortest travel routes.

Keywords: genetic algorithms; simulated annealing; Taiwan; Taoyuan

1. Introduction

Ecotourism route planning is an aspect of tourism resource management. The primary reason why economic travel itineraries are selected for tourist attractions is to reduce greenhouse gas (GHG) emissions generated from transportation [1–4] and create green tour packages. These itineraries include appropriate ratios between traffic transit and recreation time for isolated attractions. This type of planning is a form of tourism that minimizes the effects of conventional mass-package tourism for destinations in natural environments. This practice also facilitates tourist experiences using an environmentally friendly travel-route design that respects vulnerable road ecology [5–8]. Natural scenery often motivates visitors to discover viewing sites based on sound route planning. However, few studies have reported how to solve problems and save on traffic transit times to conserve energy in ecotourism route planning.

Some people are unconcerned with saving energy; they may take unplanned detours because of a poor sense of direction, or have a propensity to waste fuel during meandering trips. When applying travel-route planning to ecotourism, shortest-route analysis modules—that is those created with the help of computer-aided networks—are used to solve time-consuming travel situations, as in the classic Traveling Salesman Problem (TSP) [9–11]. Based on the results of route network analysis, this approach provides optimal results for travel route planning to determine the shortest distance and time, and the lowest cost for transportation fuel savings [2,12–14]. These savings lead to reduced gasoline combustion, thereby decreasing carbon emissions; therefore, transportation distance, transportation speed, and loading weight can be adjusted to solve pollution-routing problems [15].

Because of the rapid progress of computer processing power rather than personal programming, route planners can use various types of algorithms through computer-aided operations to search for optimal solutions within time and distance constraints. The algorithms calculate travel distance and travel time from starting points, return routes, and endpoints of local transportation. Furthermore, computing integrated with the geographic information systems (GIS) implementations can benefit from the integration of more robust optimization techniques [16]. Network data structures were one of the representations of GIS and has been used in geographic information science (GIScience) [17,18]. Network studies have applied two algorithmic approaches, simulated annealing (SA) and genetic algorithms (GA), to obtain optimal solutions. GAs originated in the 1950s with biologist Alex Fraser, who simulated artificial selection [19]. He used GAs to select a holistic-interactive mutual search by using a paired approach to improve calculation velocities and appropriate paths, attempting to optimize genetic evolution. Based on the behavioral simulation of biological evolution, GAs share the concept of mutation in chromosomal DNA through arithmetic encoding and selection [20,21]. This approach has facilitated a successful path analysis. Therefore, this method has been applied in operating travel schedules, with an optimization focus on travel management within tourism-demand forecasting [22]. The original concept of the SA algorithm was first reported by Metropolis *et al.* [23], followed by Kirkpatrick *et al.* [24]. The assumption of the SA algorithm is that when a solid matter is heated to a certain temperature, the change from solid type to a liquid type neutralizes this object. When the cooling process is controlled to a completely cooled type, this process is rearranged as an expected stable crystal type. The SA algorithm solves the type that moves to a lower target value as the object of a cooling crystallization process [25–27]. The final crystalline pattern becomes a new solution. When the current situation falls into a local optimum, the metal is heated to cause the atoms to move from their original position to reach a higher position from the optimal solution. Previous heuristic solutions have focused on using artificial intelligence (AI) and GAs. However, the SA application has received less attention in studies of heuristic solutions [28]. Therefore, SA and GA both can be applied in the study of optimal route planning. However, determining which algorithms might be more advantageous for obtaining the optimal solution is important. In this study, we applied two algorithms in our simulation research to address the following question: "what is an appropriate algorithm for running smaller or larger carbon-routing algorithms at the regional scale?"

2. Experimental Materials and Methods

2.1. Research Materials

This study focused on avian tourism for bird watchers, with the aim of achieving optimal satisfaction regarding greater biodiversity in bird-watching attractions. Therefore, bird-watching locations were used as the study area. Bird-watching activities in Taiwan began in the 1970s, and occur predominantly in biological hotspots that play host to relatively high avian biodiversity. Because this is a popular ecotourism activity, routine bird watching of similar species at fixed locations might prove to be unsatisfactory. Bird watchers prefer to travel by cars to seek out viewing more birds in different great places. Unfortunately, this consideration is beyond the ecotourism concept, low carbon footprint, regarding repeated vehicle routes among various birding attractions, which can be time-consuming, laborious, and involve inefficient transportation. Therefore, we considered how a bird watcher can continue to enjoy birding at the optimal level without creating a negative carbon footprint, which is crucial to activity satisfaction.

In this study, 45 pond surveys were carried out on numerous wintering bird species in Taoyuan, Taiwan from December 2008, January 2009, and February 2009. The Taoyuan region is located on a 323-km^2 plateau that is home to one-fifth of all avian species in Taiwan [29]. Surveys were conducted to be beginning as early as 30 min before sunrise to 3 h following sunrise. The scientific concerns of the study were focused on the diurnal birds which roost and sleep at night. They become principally active when the sun rises. Therefore, we did not count owls, but count songbirds, waterfowl, as well as raptors. Several prerequisites were stated such as: (a) these farm ponds are not located in a national park or other protected area; (b) the field studies did not involve endangered or protected species, sampling data were collected from a 100–200-m distance, and no animals were harmed or disturbed; and (c) no specific permission was required for these farm-pond surveys because the area has contained over 3000 ponds for over 100 years, which are maintained by the Taoyuan Irrigation Association and the Shihmen Irrigation Association to be open and free to the public.

To enjoy its rich bird-watching attractions and artificial farm ponds, bird watchers must overcome a complex network of isolated pond configurations. Therefore, this study developed a model with the aid of a geographic information system (GIS) to collect avian diversity, and through geographic distribution and route network analysis, determined the optimal bird-watching hotspots. Based on various locations for bird-watching, this study applied SA and GA algorithms to determine priority routes, as shown in Figure 1.

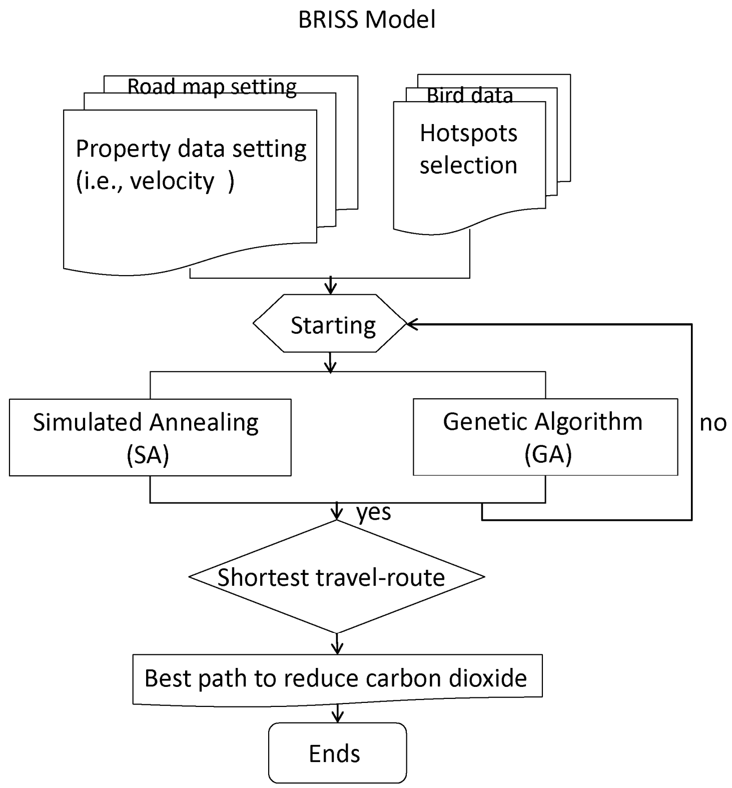

Figure 1. The conceptual flow chart of the Bird-watching Route Information Support System Model.

2.2. Research Methods

2.2.1. Diversity Calculation

We studied and calculated bird diversity at each pond by using the Shannon diversity index (H') [29,30]. These ponds are regarded as biological hotspots for bird watchers, and H' is commonly used to characterize species diversity in avian communities [31]. H' accounts for both the abundance and evenness of the species present. The proportion of species (*i)* relative to the total number of species (P_i) was calculated and subsequently multiplied using the logarithm of this proportion, ($\log_2 P_i$). The resulting product was summed across species, and multiplied by −1:

$$H' = -\sum_{i=1}^{s} P_i \log_2 P_i \quad (1)$$

where S is avian species richness and P_i is the percentage of species *i* in the avian community.

Before we applied the Bird-watching Route Information Support System (BRISS), we recorded the latitude and longitude of the pond location. Road maps have been digitized and overlapped with biological hotspot maps through ArcGIS 8.3 and Super GIS 2.2. A higher value of the Shannon–Wiener index (>2) was selected. This was designed so the bird watchers could enjoy the richness and abundance of bird species at above-average values in the Shannon–Wiener index during certain periods (*i.e.*, weekends). We applied SA and GA using Super GIS 2.2 in route analysis as follows.

2.2.2. SA Calculation

Using the SA algorithm, when temperature (T) increases, the solution obtained in this case is nearly random; however, a stabilized solution can be obtained with a slowly cooling T [32]. A slow cooling rate provides more opportunities to obtain the optimal solution [33]. We, thus, defined that the SA application is similar to the process regarded as a "randomized variation" of the solution search approach [28]. The fundamental principle of solution search is an iterative process, which starts with an initial or a current solution and finds a solution neighborhood for a new solution. If the new solution is found, it takes the place of the current solution. On the contrary, the algorithm creates a locally optimal solution. The probability function is as follows:

$$P(S') = \begin{cases} 1, & \text{if } f(S') \le f(S) \\ \exp\left(\dfrac{-|f(S') - f(S)|}{T}\right), & \text{if } f(S') > f(S) \end{cases} \quad (2)$$

S: Current solution
S': New solution
$f(S)$: Current energy state which is determined by function
$f(S')$: Next energy state which is determined by function
T: Temperature

When $f(S') \le f(S)$, the new solution is considered an improved solution. If this new provisional state is accepted, then we set the provisional state as the new solution. It means that new solution (S') is better than that of current solution (S). When the gap between $f(S')$ and $f(S)$ widens, this evolution function is designed to generate a likelihood for a decreasing solution. The relationship between $f(S')$ and $f(S)$ is dependent on their variation; the smaller the difference between $f(S')$ and $f(S)$, the greater the likelihood of a new solution being accepted [23,24] , such as the following codes:

Procedure Simulated Annealing;
{General form of a SA optimization}
$f(S) := f(S)_0$; {Starting value}
Initialize heuristic parameters; repeat
$f(S') :=$ perturb $f(S)$;
If accept $f(S')$, then $f(S) := f(S')$;
Until "time to adapt parameters";
Adapt parameters until "terminating criterion";
End.

2.2.3. GA Calculation

The theory of GAs is well known which requires tasks to be assigned to proxy from corresponding groups at minimum total cost, subject to resource limitations for each proxy [34]. Based on the concepts borrowed from natural selection and natural genetics, the algorithm is both aimed at minimizing the total distance (as "total cost" and/or "total travel time") and at minimizing temporal constraint violations [32,33]. In this case where the birders are located in the beginning point, they are sorted according to a nearest neighbor solution as fit solution. Next, we apply this process of effecting reproduction for GAs to generate new solutions that fit certain route patterns from a higher "target value". We formed an objective function to establish a target value for assessing how corresponding groups of chromosomes work with the corresponding function, and to clarify the degrees of the "corresponding value" to analyze the adaptation target value. We then selected a case according to the first step of corresponding value. The higher the target value, the higher the corresponding value that could be selected. We described the numbers of different species that are presented in the form:

$$\dot{x}_i = x_i f_i(\underline{x}) \tag{3}$$

where x_i is the numbers of species i, f_i its fitness and there are n species in total.

We tried to use precise solution to find corresponding value with this reproducing system for (n + 1) types given by

$$y_i = \frac{x_i}{X+1}, i = 1,...,n \quad y_{n+1} = \frac{1}{X+1} \tag{4}$$

We supposed there are mutations in the reproduction process; then the probability (q_{ij}) of type j mutating to type i should be obtained by

$$\dot{y}_i = \sum_{j=1}^{n} y_j f_j(\underline{y}) q_{ji} - \bar{f}(\underline{y}) y_i \tag{5}$$

GAs plays the role of a local search operator to look for the sequence of spots for the improvement of the low-carbon birding tour. They operate with a population of heuristic solutions iteratively by successively exploiting three essential genetic operators—selection, crossover, and mutation—until a termination criterion is satisfied [10]. In this case, each chromosome has an optimum value which is the summation of the birding-travel times represented by the chromosomes which are themselves interval numbers. When the crossover proportion was detected to have a much higher genetic recombination rate than that of the mutation, the probability of retaining improved chromosome ingredients decreased. However, when the probability of mutation was detected to be much more with less genetic recombination, the result was random.

Therefore, the generation selection approach was used at this stage to determine Attractions A (both parents) and Attractions B (their children) to determine the next generation for gene operation, such as the following codes: (1) crossover by a single cut-point; (2) crossover by dual cut-points; (3) crossover by a random mask; and (4) mutation (Figure 2). Our proposed algorithm consists of three characteristics on initialization, such as selection, crossover, and mutation. Each gene of the chromosome is appointed a random number drawn between 0 and 1 for all members of the population. In this process, the genetic structure of routes in the neighborhood was alternated from variants which were based upon the resection and reinsertion. Finally, the results of computational processes on various GA mutation have been reported. Here, the optimistic decision for a traveling route is to be considered.

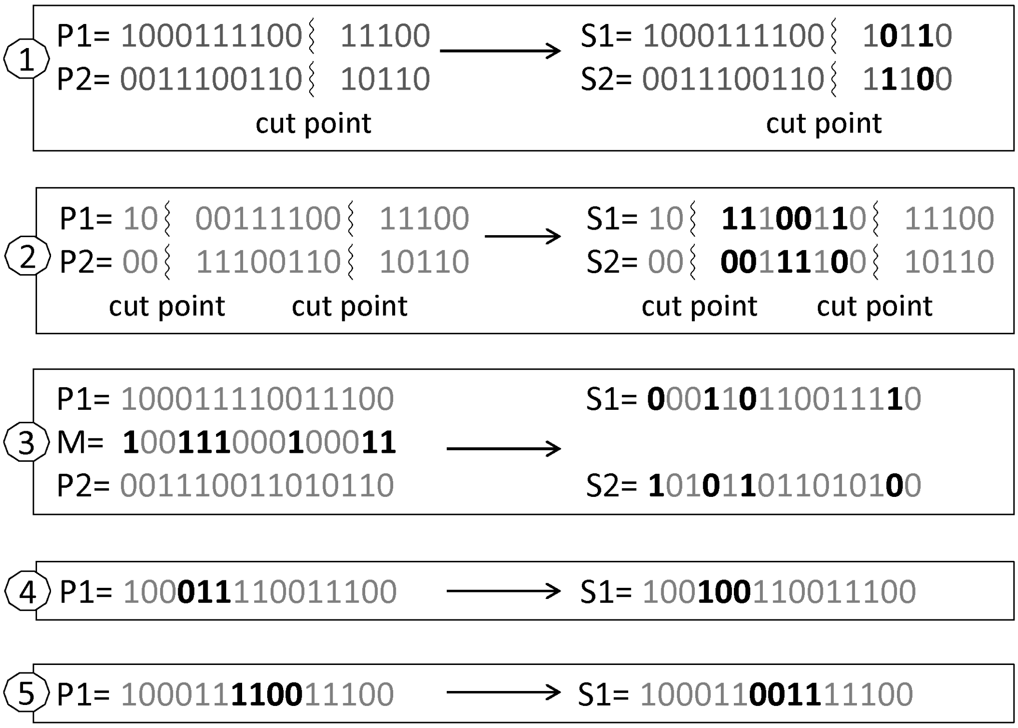

Figure 2. Matching approach for genetic algorithms. P1: parent 1; P2: parent 2; S1: children 1; S2: children 2; M: mask. The numbers of 1~4 represent: (1) crossover by single cut-point; (2) crossover by dual cut-points; (3) crossover by a random mask; and (4) mutation. The processes of No. 1 to No. 3 are couple matching in pairs from crossover functions (also called recombination). No. 4 represents one of the types of mutation. (Revised from Man *et al.* [34]).

Initialize population;
Sum + = fitness of all individuals;
End for
For all members of population
Evaluate population;
Probability = sum of probabilities plus (fitness / sum)
Sum of probabilities + = probability
End for
While termination criteria not satisfied
Select parents for reproduction;
Loop until new population is satisfied for this solution
Try this twice
Number = random between 0 and 1 for all members of population
If number > probability but less than next probability then
This has been selected

End for
End
Perform recombination and mutation;
Create offspring
End loop

3. Results and Discussion

3.1. Results

Our wintering bird survey identified 79 species with a total sample size of 11,623 birds. The 79 bird species were comprised of 44% wintering, 41% resident, 8% transient, 5% exotic, and 3% vagrant birds during the 2008–2009 collecting period. In January 2009, we detected that the cumulative amount of avian richness and abundance in all 45 ponds was greater than it was for the other two months. The cumulative number of birds was categorized as 52% resident, 47% wintering, and 1% winter birds (the latter comprised of transient, exotic, or vagrant birds). The top 10 birds accounted for 76% of the total, such as the Grey Heron (*Ardea cinerea*; 1686; 15%); Tufted Duck (*Aythya fuligula*; 1652; 14%); Little Egret (*Egretta garzetta*; 1169; 10%); Black-crowned Night-heron (*Nycticorax nycticorax*; 1082; 9%), Chinese Bulbul (*Pycnonotus sinensis*; 1002; 9%); Great Egret (*Ardea alba*; 888; 8%); Eurasian Tree Sparrow (*Passer montanus*; 493; 4%); Pacific Swallow (*Hirundo tahitica*; 375; 3%); Red Turtle Dove (*Streptopelia tranquebarica*; 241; 2%); and Barn Swallow (*Hirundo rustica*; 225; 2%) (see Table 1). The remaining 69 species accounted for 24% of the total. The cumulative number of 13 species of birds was detected more than 100 times, and some cumulative numbers of 27 species of rare birds were detected less than 10 times.

Table 1. Top 10 birds accounted for 76% of the total between December 2008 and February 2009. Our wintering bird survey identified 79 species with a total sample size of 11,623 birds.

Common Name	Scientific Name	Individual Number	Ratio
Grey Heron	*Ardea cinerea*	1686	15%
Tufted Duck	*Aythya fuligula*	1652	14%
Little Egret	*Egretta garzetta*	1169	10%
Black-crowned Night-heron	*Nycticorax nycticorax*	1082	9%
Chinese Bulbul	*Pycnonotus sinensis*	1002	9%
Great Egret	*Ardea alba*	888	8%
Eurasian Tree Sparrow	*Passer montanus*	493	4%
Pacific Swallow	*Hirundo tahitica*	375	3%
Red Turtle Dove	*Streptopelia tranquebarica*	241	2%
Barn Swallow	*Hirundo rustica*	225	2%
		8813	76%

The numbers of farm ponds with avian diversity (H') greater than 2 were listed between December 2008 and February 2009 (see Table 2). The data were demonstrated the aforementioned ponds which values of avian diversity (H') exhibited variable and complex patterns. Based on the locations (7) in December 2008, the locations (7) in January 2009, and the locations (14) in February 2009, this study applied SA and GA.

Tables 3–5 show the final results of shortest routes of travel distances, travel time, and carbon emissions from SA and GA for December 2008, January 2009, and February 2009, respectively. For the simulation shown in Figures 3–11, the vehicle velocity was set to approximately 40 km/h throughout this route based on the Bekta and Laporte experiments in the United Kingdom [2]. In December 2008, after SA applications, the seven ponds (No. 0 to No. 6) accounted for travel distances of 59.71 km (Figure 3), at a travel time of 1 h 18 min and 19 s, with carbon emissions set to 4.84 kg. When we applied GA to the same ponds in the same periods, the travel distances (Figure 4), travel time, and carbon emissions were the same as the SA application. However, the actual GPS navigation routes accounted for greater distances by 62.08 km (Figure 5), at an actual travel time of 1 h 20 min and 28 s, which was estimated to release more carbon emissions.

Table 2. The numbers of farm ponds with avian diversity (H') greater than 2 between December 2008 and February 2009.

December 2008		January 2009		February 2009	
No. 0	2.522	No. 7	2.351	No. 14	2.575
No. 1	2.152	No. 8	2.267	No. 15	2.528
No. 2	2.128	No. 9	2.259	No. 16	2.516
No. 3	2.127	No. 10	2.205	No. 17	2.360
No. 4	2.062	No. 11	2.134	No. 18	2.357
No. 5	2.057	No. 12	2.123	No. 19	2.320
No. 6	2.022	No. 13	2.038	No. 20	2.312
				No. 21	2.282
				No. 22	2.281
				No. 23	2.219
				No. 24	2.145
				No. 25	2.046
				No. 26	2.042
				No. 27	2.007

Table 3. SA and GA applications from the ponds of No. 0–6 during December 2008.

Simulated Annealing Algorithm (SA)					Genetic Algorithm (GA)				
S.	E.	Travel Dist. (km)	Travel Time	Carbon Emissions (kg)	S.	E.	Travel Dist. (km)	Travel Time	Carbon Emissions (kg)
0	1	10.91	14m49s	0.88	0	1	10.91	14m49s	0.88
1	3	7.98	9m23s	0.65	1	3	7.98	9m23s	0.65
3	2	6.62	9m12s	0.54	3	2	6.62	9m12s	0.54
2	5	15.38	22m7s	1.25	2	5	15.38	22m7s	1.25
5	4	10.33	11m44s	0.84	5	4	10.33	11m44s	0.84
4	6	8.49	11m4s	0.69	4	6	8.49	11m4s	0.69
Totals		59.71	1h18m19s	4.84	Totals		59.71	1h18m19s	4.84

Notes: 1. S.: Starting point; E.: End point; Travel Dist.: Travel Distance; h: hours; m: minutes; s: seconds. 2. If a car runs for one kilometer, this car leads emissions of 81 grams (g) of CO_2.

Table 4. SA and GA applications from the ponds of No. 7 − 13 during January 2009.

Simulated Annealing Algorithm (SA)					Genetic Algorithm (GA)				
S.	**E.**	**Travel Dist. (km)**	**Travel Time**	**Carbon Emissions (kg)**	**S.**	**E.**	**Travel Dist. (km)**	**Travel Time**	**Carbon Emissions (kg)**
7	8	12.67	16m40s	1.03	7	8	13.63	16m12s	1.10
8	9	12.34	15m15s	1.00	8	9	15.00	20m0s	1.22
9	10	12.08	17m14s	0.98	9	10	11.60	16m40s	0.94
10	11	3.85	5m1s	0.31	10	11	2.90	3m49s	0.23
11	12	15.86	21m36s	1.28	11	12	16.48	22m23s	1.33
12	13	20.19	27m11s	1.64	12	13	20.17	27m10s	1.63
Totals		76.99	1h42m57s	6.24	Totals		79.78	1h46m14s	6.46

Notes: 1. S.: Starting point; E.: End point; Travel Dist.: Travel Distance; h: hours; m: minutes; s: seconds. 2. If a car runs for one kilometer, this car leads emissions of 81 grams (g) of CO_2.

Table 5. SA and GA applications from the ponds of No. 14–27 during February 2009.

Simulated Annealing Algorithm (SA)					Genetic Algorithm (GA)				
S.	**E.**	**Travel Dist. (km)**	**Travel Time**	**Carbon Emissions (kg)**	**S.**	**E.**	**Travel Dist. (km)**	**Travel Time**	**Carbon Emissions (kg)**
14	15	2.12	2m32s	0.17	14	15	2.12	2m32s	0.17
15	16	13.04	17m47s	1.06	15	16	13.04	17m47s	1.06
16	17	3.69	4m46s	0.30	16	17	3.69	4m46s	0.30
17	18	1.33	1m54s	0.11	17	18	1.56	2m13s	0.13
18	19	2.00	2m29s	0.16	18	19	2.27	2m51s	0.18
19	20	4.17	6m5s	0.34	19	20	4.41	6m24s	0.36
20	21	7.24	10m19s	0.59	20	21	7.34	10m30s	0.59
21	22	8.13	11m42s	0.66	21	22	8.13	11m42s	0.66
22	23	6.12	7m51s	0.50	22	23	6.12	7m51s	0.50
23	24	2.13	3m7s	0.17	23	24	2.25	3m14s	0.18
24	25	5.11	6m36s	0.41	24	25	5.11	6m36s	0.41
25	26	13.42	18m35s	1.09	25	26	12.77	17m46s	1.03
26	27	20.17	27m10s	1.63	26	27	20.05	26m58s	1.62
Totals		88.67	2h0m17s	7.18	Totals		88.86	2h1m10s	7.20

Notes: 1. S.: Starting point; E.: End point; Travel Dist.: Travel Distance; m: minutes; s: seconds. 2. If a car runs for one kilometer, this car leads emissions of 81 grams (g) of CO_2.

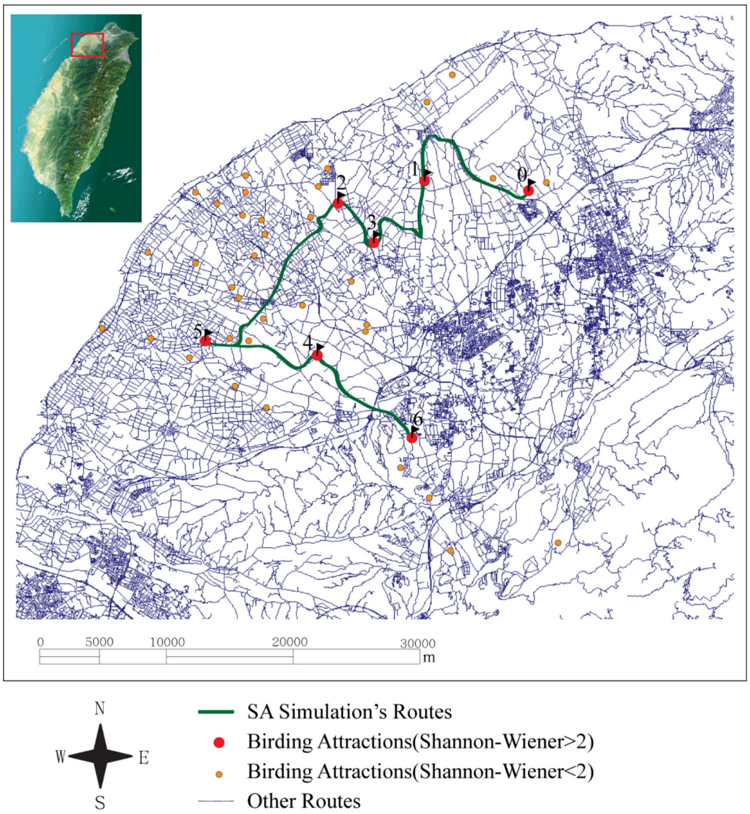

Figure 3. The SA applications accounted for the travel distance of 59.71 kilometers (km) at a travel time of 1 h 18 min and 19 s from the ponds of No. 0–6 during December 2008.

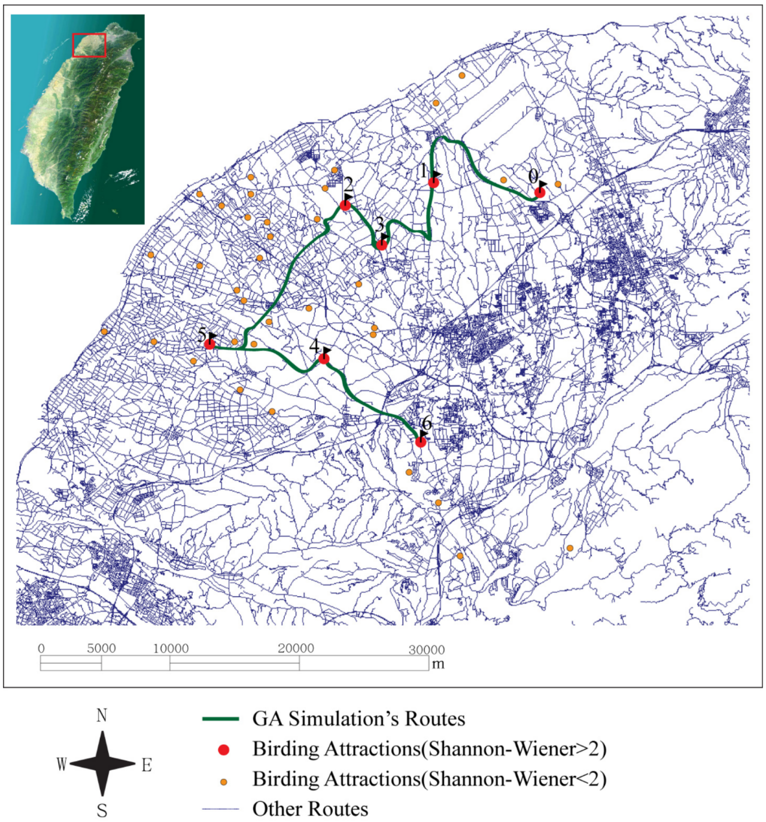

Figure 4. The GA applications accounted for the travel distance of 59.71 kilometers (km) at a travel time of 1 h 18 min and 19 s from the ponds of No. 0–6 during December 2008.

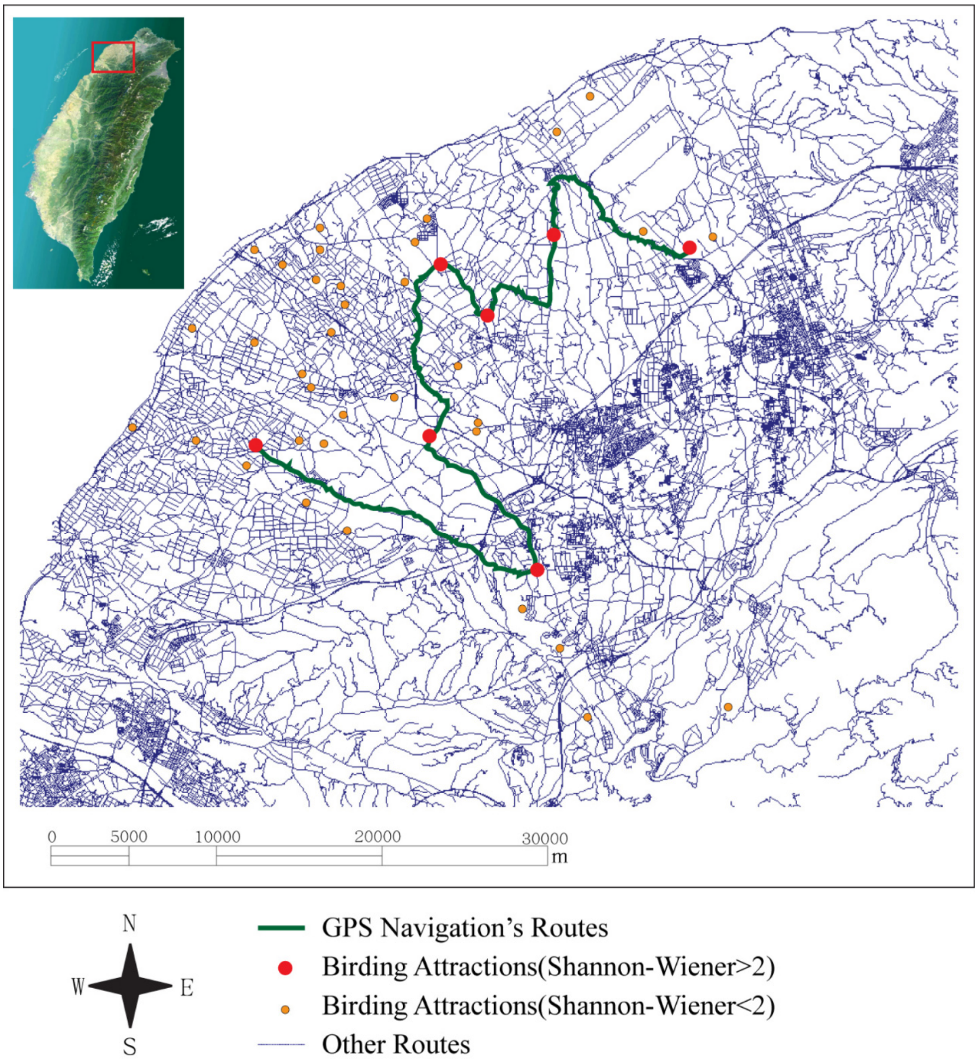

Figure 5. A real GPS navigation routes accounted for the travel distance of 62.08 kilometers (km) at a travel time of 1 h 20 min and 28 s from the ponds of No. 0–6 during December 2008.

In January 2009, after SA applications, the seven ponds (No. 7 to No. 13) accounted for the travel distances of 76.99 km (Figure 6), at a travel time of 1 h 42 min and 57 s, for which carbon emissions were 6.24 kg. After GA applications, the seven ponds also accounted for travel distances of 79.78 km (Figure 7), at a travel time of 1 h 46 min and 14 s, for which carbon emissions were 6.46 kg. When SA and GA were applied to the same ponds in the same periods, the SA result was superior to that of GA in shorter travel distance (2.79 km), less travel time (3 min and 17 s), and lower carbon emissions (0.22 kg). Comparing SA to GA applications, SA achieved a 3.41% greater reduction in carbon emissions than did GA. However, the actual GPS navigation routes accounted for greater travel distances at 92.2 km (Figure 8), with an actual travel time of 2 h 3 min 50 s, which was estimated to release more carbon emissions.

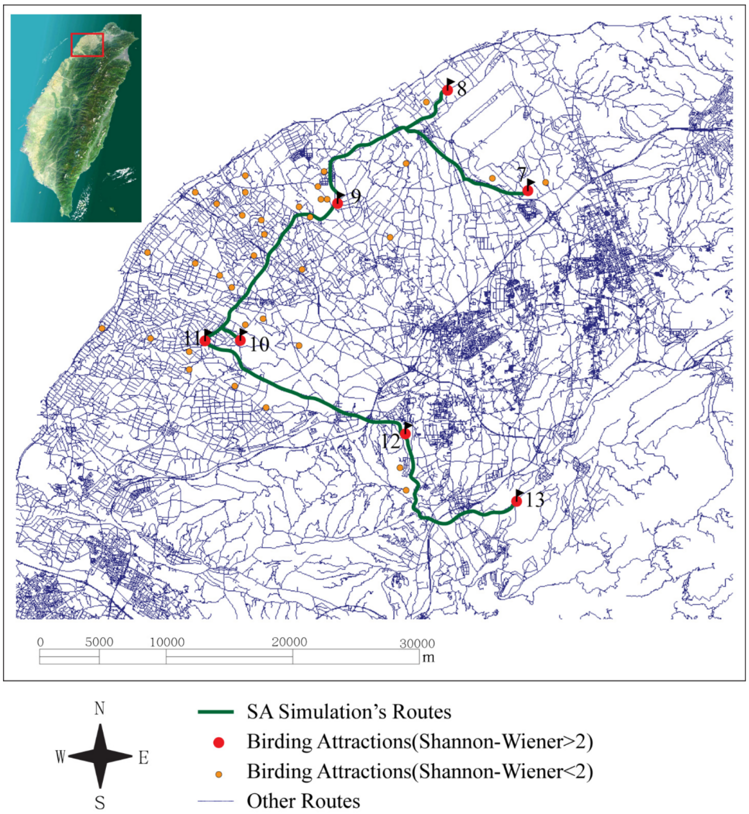

Figure 6. The SA applications accounted for the travel distance of 76.99 kilometers (km) at a travel time of 1 h 42 min and 57 s from the ponds of No. 7–13 during January 2009.

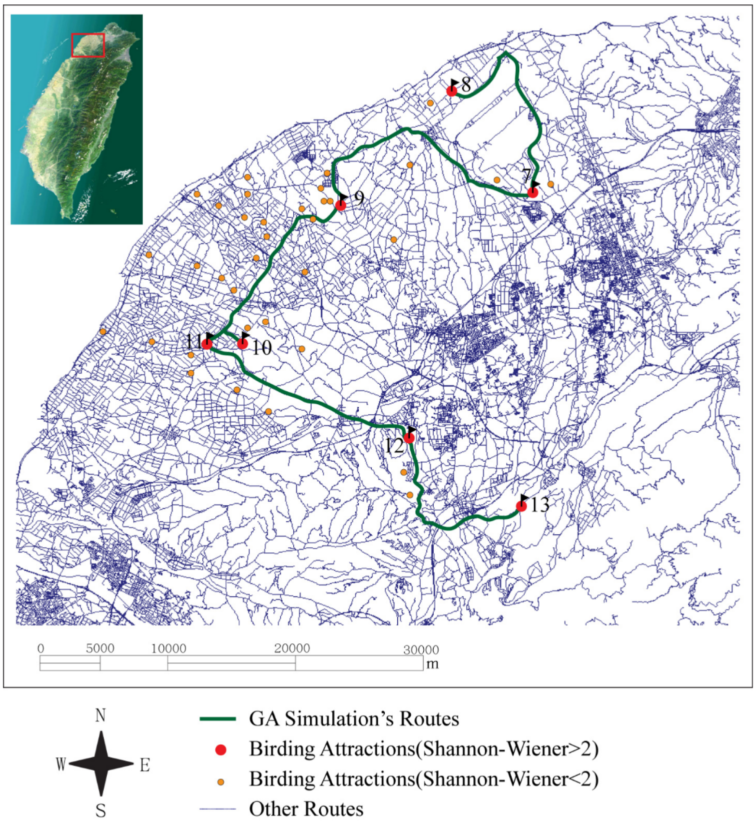

Figure 7. The GA applications accounted for the travel distance of 79.78 kilometers (km) at a travel time of 1 h 46 min and 14 s from the ponds of No. 7–13 during January 2009.

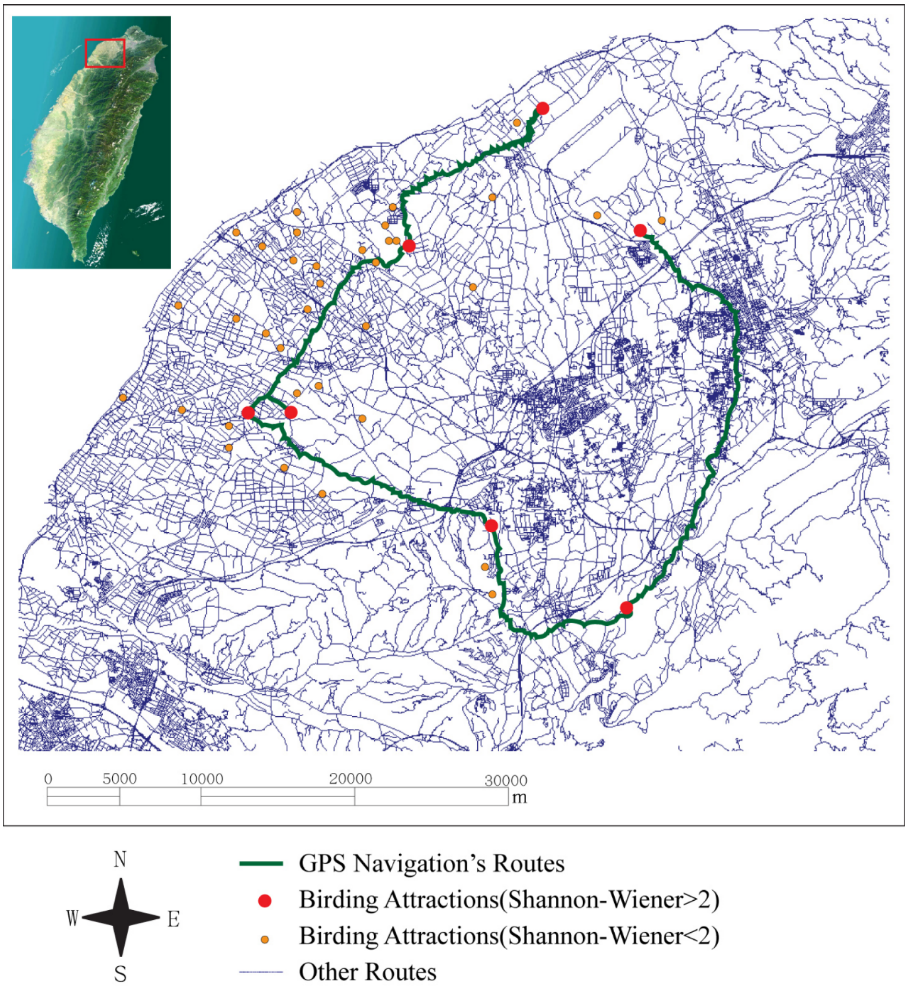

Figure 8. A real GPS navigation routes accounted for the travel distance of 92.2 kilometers (km) at a travel time of 2 h 3 min and 50 s from the ponds of No. 7–13 during January 2009.

In February 2009 period, after SA applications, the 14 ponds (No. 14 to No. 27) accounted for travel distances of 88.67 km (Figure 9), with a travel time of 2 h and 17 s, for which carbon emissions were 7.18 kg. After GA applications, the 14 ponds accounted for travel distances of 88.86 km (Figure 10), with a travel time of 2 h 1 min and 10 s, for which carbon emissions were 7.20 kg. Using SA and GA applications for the same ponds in the same periods, the SA result was slightly superior to that of GA at a shorter travel distance (0.19 km), less travel time (53 s), with lower carbon emissions (0.02 kg). Comparing SA to GA applications, SA achieved a 0.28% greater reduction in carbon emissions than did GA. However, the actual GPS navigation routes accounted for greater travel distances of 94.3 km (Figure 11), with an actual travel time of 2 h 2 min and 40 s, which was estimated to release more carbon emissions.

In summary, the results of the BRISS demonstrated that both the SA and GA applications produced similar solutions for optimal path planning. However, the SA application led to more opportunities for obtaining optimal solutions when compared with the results from the GA application.

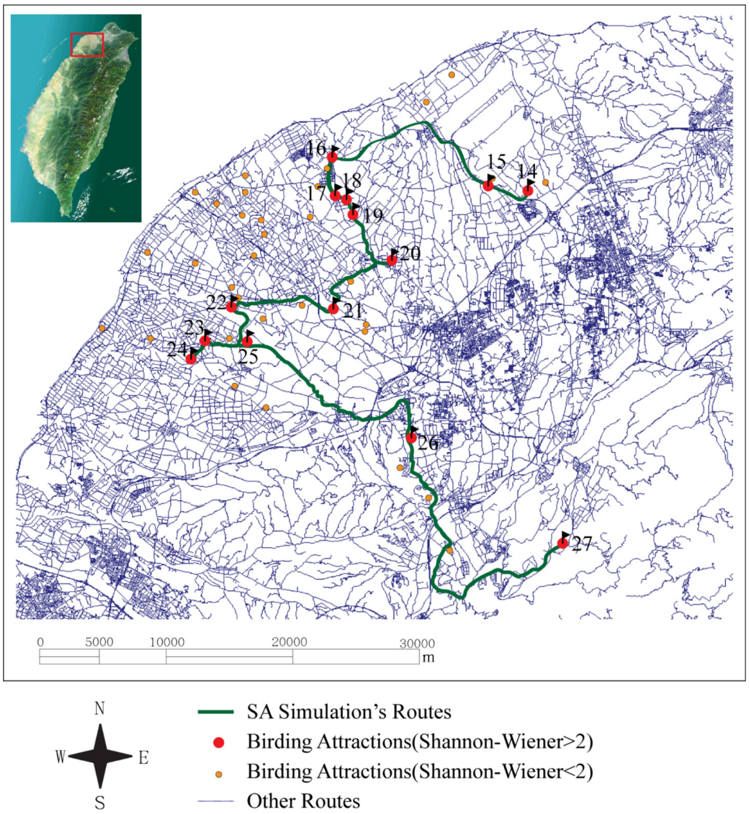

Figure 9. The SA applications accounted for the travel distance of 88.67 kilometers (km) at a travel time of 2 h and 17 s from the ponds of No. 14–27 during February 2009.

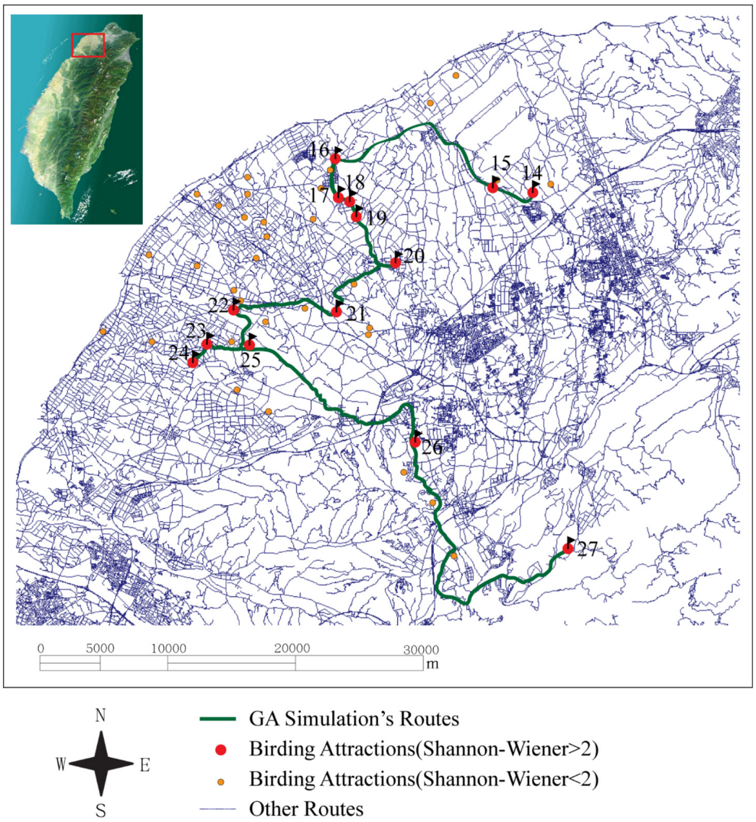

Figure 10. The GA applications accounted for the travel distance of 88.86 kilometers (km) at a travel time of 2 h 1 min and 10 s from the ponds of No. 14–27 during February 2009.

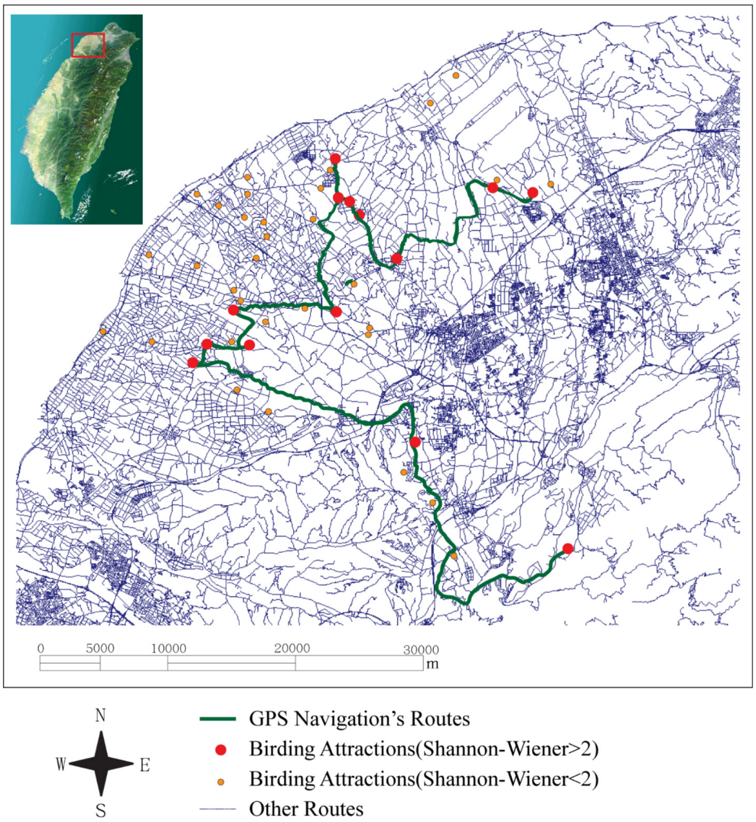

Figure 11. A real GPS navigation routes accounted for the travel distance of 94.3 kilometers (km) at a travel time of 2 h 2 min and 40 s from the ponds of No. 14–27 during February 2009.

3.2. Discussion

3.2.1. Behaviors of Birds and Bird Watchers

This study has been considered both for the behaviors of birds and bird watchers. This study would benefit from taking into account the differences in bird diversity and abundance at each farm pond during migration season. The behavior of the passerine birds (e.g., Eurasian Tree Sparrow, *Passer montanus*) is quite different from the waterbirds (e.g., Grey Heron, *Ardea cinerea*). The waterbirds congregate at wetland sites, while birds like Red Turtle Doves (*Streptopelia tranquebarica*) always gather in small groups. In this case, most passerine birds are more active 3 h before sunrise and about 3 h before sunset. However, these surveys were conducted as early as 30 min before sunrise to 3 h following sunrise according to bird-watchers' behaviors. The scientific rigor of the study was focused on the diurnal birds which roost and sleep at night, especially waterbirds. In the farm ponds, waterbirds demonstrate daily patterns for foraging as the sun rises in the early morning. In addition, bird watchers prefer to see gregarious species gather in large groups that are easier to search for and identify during wintering migration in Taiwan. Daily bird watching during wintering makes it easier to observe waterbirds from a safe distance in pond areas. This survey, thus, facilitates in providing unique opportunities for bird watchers, helping bird watchers to save time, enjoy their journey and reduce carbon dioxide and high gasoline fees while traveling between bird watching spots.

3.2.2. Model Formation

Based on multiple uses of algorithms, the SA application obtained shorter distances with lower carbon emissions compared with that of GA. This reduced emission aligned with ecotourism expectations is in line with bird-watching aims for a design of low carbon footprint routes. Table 4 shows that the reduced carbon ratio was calculated at 3.41% in GA and SA applications, possibly because Starting Point 7 and End Point 8 were isolated from the Taoyuan International Airport (referred to as TPE). Although this BRISS model encountered enormous traffic route obstacles, SA has been selected to enhance computing skills to detour around the obstacles through the shortest path of No. 7 to No. 8, and from No. 8 to return back to No. 9. Both distances from No. 7 to No. 9 were calculated at 3.62 km between SA and GA applications. The SA application was calculated to reduce 0.29 kg of carbon emissions with a lower fuel cost from GA application from the routes between No. 7 and No. 9. Xiao *et al.* [32] also examined this situation to explain why uneven geographical positions have an influence on fuel cost savings in a similar model. Xu *et al.* [35,36] found continual network-design problems (CNDP), and declared that if demand is large, SA is more efficient than GA. However, when demand is light, GA is currently able to achieve a more optimal solution.

In this study, we set the GA application to deploy crossover and mutation to reach a certain ratio by each aforementioned approach. This is the dilemma in running the BRISS model to employing a probability ratio precisely between crossover and mutation within a limited time. When using the GA application in the BRISS model to determine superior route planning for solving the carbon-routing problem, previous other studies have considered applying weight values and a time window for advancing evolutions in each application [37–40]. However, the GA application was intended to obtain a partial optimal solution in some areas, but not to be considered an optimal solution of the entire applied region [41]. A GA recombination rate that is too high might lead to premature convergence to a local optimal result that is beyond the regional optimal result [42]. This would cause a loss in the capability to find the most suitable solution in the entire area, and we could increase the mutation rate to achieve an enhanced optimal solution [43]. Therefore, applying GA may be an enhanced solution rather than an optimal solution in designing the route network in the BRISS program. Numerical results from Fan and Machemehl [28] have demonstrated that the proposed SA outperformed the GA in most cases in their models. Liu *et al.* [44] also argued that the GA runtime is typically much longer.

To mitigate these shortcomings, more advanced studies for diverse path problems should involve lower overall distances and emphasize saving computational time by improving model qualities with hybrid GA/Tabu [45], GA/particle swarm optimization [46], GA/fuzzy [47], GA/ time windows [48,49], SA/fuzzy [50], SA/time windows [37–40], SA/Tabu [51–53], and advanced evolutionary algorithms [44].

4. Conclusions

This study successfully used SA and GA applications to solve carbon polluted-routing problems for bird watchers in farm-pond areas across Taoyuan, Taiwan. The solutions for bird watchers were also presented in the form of an optimal algorithm derived from BRISS to generate carbon-reduced route maps automatically at a regional scale. Because of the growing popularity of bird watching as a recreational activity in Taiwan, using our BRISS programs to plan bird-watching routes saves energy.

Because of the difficulties in planning one-day birding trips, this study was focused on finding an ideal computer-aided program design to assist in personalized trips for bird watchers.

The benefits of the program include a reduced total carbon footprint and streamlining of ecotourism route planning. This program supports the aims of ecotourism and green transportation to promote energy efficiency and reduced carbon emissions in line with green initiatives [54]. Our study detected the shortest distances with priority routes by using SA, which is superior to GA. However, the solution performance was affected by a number of factors [55], and more realistic factors will be considered for advanced studies of this model. The BRISS application assisted bird-watching tourists in their route planning. By using ecotourism route planning, future route planners can further increase their capabilities by determining optimal routes for bird-watching recreation activities.

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Author Contributions

Conceived and designed the experiments: Wei-Ta Fang Performed the experiments: Wei-Ta Fang Analyzed the data: Wei-Ta Fang, Jui-Yu Chou Contributed reagents/materials/analysis tools: Wei-Ta Fang, Chin-Wei Huang, Jui-Yu Chou, Bai-You Cheng, Shang-Shu Shih.

Conflicts of Interest

The authors declare no conflict of interest.

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