Research on Global Illegal Wildlife Trade Based on Integrated Optimization Methodologies

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Abstract. To help improve the situation at this stage of the illegal wildlife trade, this article takes a comprehensive look at global data on Illegal Wildlife Trade (IWT) based on the background that illegal wildlife trade is still rampant at this stage. Through data-driven as well as mathematical modeling, feasible and effective measures are proposed. Firstly, we analyze the massive data through deep learning techniques, and neural networks are used to predict the subsequent trend of illegal wildlife trade. Immediately after that, we give two scenarios. The first is to stimulate people's awareness of protection through global advocacy, we establish a mathematical model of travelers, and the simulated annealing algorithm is used to solve the optimal routes, which gives the specific routes of global advocacy. Secondly, we analyze the important nodes of the global illegal wildlife trade, model the planning problem based on the greedy strategy, establish the global monitoring measures, and give the location of the corresponding monitoring points. Overall, we provide a general assessment of the global illegal wildlife trade and provide specific and feasible means to suppress it.

Keywords: BP Neural Network, Traveling Salesman Problem, Greedy Strategy.

1. Introduction

Due to the high global consumer demand for wildlife for medicinal purposes and other aspects [1], IWT is already worth up to $26.5 billion annually. IWT reduces biodiversity, has irreversible negative impacts on the environment [2], and can even lead to outbreaks of zoonotic diseases. Nowadays, the number of wildlife in many countries is declining rapidly and facing extinction. Therefore, we need to produce a program to reduce IWT in order to achieve peaceful coexistence between man and nature.

Since the COVID-19 outbreak, many scientists have found that zoonoses are closely linked to the IWT [3]. According to Mozer Annika, a recent study by Prost Stefan found that more than 60% of emerging infectious diseases in humans are caused by zoonoses, which kill 2.7 million people every year [4]. More than that, IWT has cascading consequences on environments, human lives and communities, national stability, and the economy. Moreover, IWT is linked to many different crimes, such as corruption, money laundering, drugs and so on [5].

Now, researchers are trying to find ways to strike a balance between economic and conservation interests to reduce IWT. Dominic Meeks, Oscar Morton, and David P. Edwards have experimented with captive breeding of wild animals [6]. Justin Kurland, Stephen F. Pires et al have proposed the establishment of protected areas and fenced barriers to reduce animal-human conflict [7].

However, the feasibility and sustainability of these approaches are open to debate. Therefore, we have made a comprehensive assessment of the poaching data from previous years and have proposed strategies to reduce this illegal behavior, i.e. the promotion of conservation wildlife route planning and the establishment of global surveillance measures can go a long way to reducing the incidence of illegal poaching. This research innovatively combines BP neural network, optimization algorithm and greedy strategy to enhance the publicity and monitoring effect of illegal wildlife trade.

2. Models

2.1. The basic fundamentals of BP neural network

BP neural network is a multi-layer feed-forward neural network that is trained by a back-propagation algorithm to minimize the error between the predicted output and the target value [8]. It usually consists of an input layer, a hidden layer, and an output layer, with each layer consisting of multiple neurons.

The computational representation of the output y_j for each neuron j is:

$$y_j = \sigma(\sum_{i=1}^{n} \omega_{ij} x_i + b_j) \tag{1}$$

Where x_i is the input value, w_{ij} is the connection weight, b_j is the deviation of the neuron, and σ is the activation function.

Calculating the loss function, for the regression problem, with mean square error:

$$E(\omega, b) = \frac{1}{2} \sum_{p=1}^{P} (d_p - y_p)^2 \tag{2}$$

Where d_p is the target value, y_p is the predicted value, P is the sample value, and M is the category value.

Update the weights:

$$\omega_{ij(new)} = \omega_{ij(old)} - \eta \frac{\partial E}{\partial \omega_{ij}} \tag{3}$$

$$b_{j(new)} = b_{j(old)} - \eta \frac{\partial E}{\partial b_j} \tag{4}$$

The chain rule is applied to compute the partial derivatives:

$$\frac{\partial E}{\partial \omega_{ij}} = \frac{\partial E}{\partial y_j} \cdot \frac{\partial y_j}{\partial \omega_{ij}} \tag{5}$$

Finally, the weights are repeatedly updated using the weight update formula described above until the stopping condition is satisfied.

The flowchart of the algorithm for the BP neural network is shown in Figure 1.

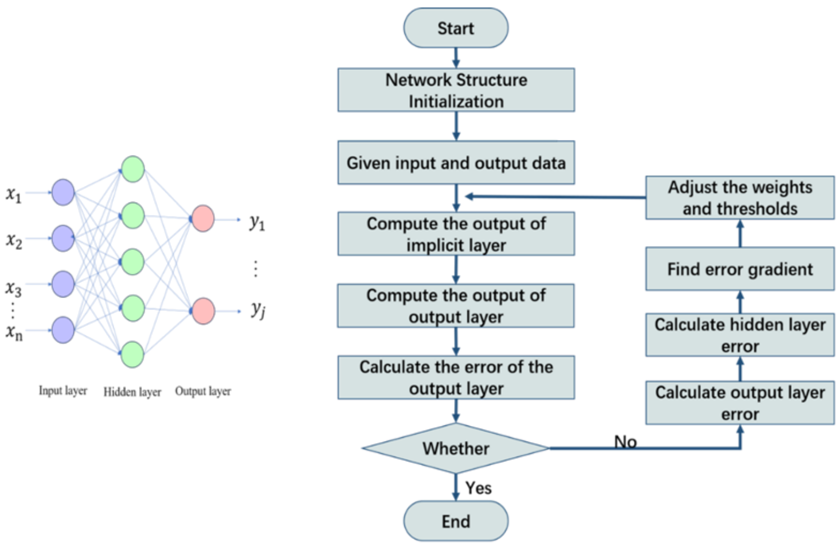

Figure 1. Flow chart of BP neural network.

2.2. TSP

Traveling Salesman Problem (TSP) is used to optimize the selection of paths for global campaigns. The goal of the TSP problem is to find the shortest path that allows travelers to pass through each city once and eventually return to the starting point. We use this approach to find the shortest path that allows the campaign delegates to visit all nodes in turn and eventually return to the starting point.

Define the set $C = \{1,2,\cdots,n\}$ to denote the cities with indexes 1 to n. The distance matrix is:

$$D = [d_{ij}] \tag{6}$$

Where d_{ij} denotes the distance from city i to city j.

Let the decision variable be x_{ij}, then

$$\begin{cases} x_{ij} = 1, & i \to j \\ x_{ij} = 0, & otherwise \end{cases} \tag{7}$$

The total travel distance is minimized, i.e., the objective function is:

$$Minimize \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} d_{ij} x_{ij} \tag{8}$$

Assuming that each city can only have one entry and one exit, for i=1, 2⋯n, there are:

$$\sum_{j=1, j \neq i}^{n} x_{ij} = 1 \tag{9}$$

The objective function to be optimized:

$$\underset{x \in X}{Minimize} \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} d_{ij} x_{ij} = \min_{x \in X} \left(\sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} d_{12} x_{12}, \sum_{i=1}^{n} \sum_{j=1,, j \neq i}^{n} d_{13} x_{13}, \cdots, \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} d_{n(n-1)} x_{n(n-1)} \right) \tag{10}$$

Define how the temperature decreases and when the annealing process stops:

$$T_{new} = \alpha T_{current} \tag{11}$$

Where $T_{current}$ is the current temperature, T_{new} is the new temperature, and α is the cooling factor, which usually takes a value less than one.

Metropolis acceptance criterion:

$$P(accept) = \exp\left(-\frac{\Delta E}{k_B T}\right) \tag{12}$$

Where ΔE is the energy change, i.e. the difference between the new objective function value and the current objective function value, T is the current temperature, and k_B is the Boltzmann constant. If $\Delta E < 0$, the new solution is accepted unconditionally.

Neighborhood search: an optimization problem in continuous space that can be formulated as adding a temperature-controlled random perturbation to the current solution:

$$x_{new} = x_{current} + \delta(x, T) \tag{13}$$

Finally, the obtained data is normalized to get the result.

2.3. Optimisation strategies for surveillance systems

Considering the different trading nodes around the globe, we can build a network of monitoring systems to achieve the control of illegal wildlife trade.

We carry out the planning model building through the greedy strategy [9]. The greedy strategy is used to optimize the establishment of the monitoring system. The greedy strategy is a step-by-step method of selecting the current optimal solution for multi-stage decision-making problems. In this according to the illegal wildlife trade data of each country, the establishment order is decided according to the size of the illegal trade volume of the country, and the priority is to establish the monitoring system in the country with larger illegal trade volume.

Define

$$V = \{v_i\}_{i=1}^{n} \tag{14}$$

Where to represent the set of individual countries in the country, where v_i denotes the ith country.

Choose k countries as monitoring points, denoted as:

$$M = \{m_j\}_{j=1}^{k} \tag{15}$$

Where $M \subseteq V$.

Maximise the amount of illegal wildlife trade in the area covered by the surveillance and set the objective function to be:

$$\max \sum_{j=1}^{k} T(m_j) \tag{16}$$

Where T (m_j) denotes the volume of illegal trade covered by monitoring point m_j.

The country with the largest current volume of illegal trade is selected as a monitoring point each time until k monitoring points have been selected.

Set the set of countries to be selected S=V, the gathering of selected monitoring points M=∅.

Repeat the following steps until the number of elements in M reaches k:

Selecting from S the country with the highest volume of illicit trade v_{max} , i.e. $v_{\max} = \arg\max_{v \in S} T(v)$.

Adding v_{max} to M, i.e. $M = M \cup \{v_{\max}\}$

Removing v_{max} from S, i.e. $S = S \setminus \{v_{\max}\}$

The coverage radius of each monitoring point is set to 1000 km, denoted as r. The coverage area of monitoring point m_j is a circular area centered on m_j with radius r.

Based on the selected monitoring points M and their coverage, the location of the global monitoring system is schematically mapped.

Calculate and assess the effectiveness of the coverage of selected monitoring points M and compare the changes in illegal wildlife trade before and after the coverage. Assess changes in global illegal wildlife trade over the next five years through modeling and forecasting.

3. Results

3.1. Trade volume forecast for the next five years

We trained the BP neural network using the number of IWTs per year over the last 40 years as the training dataset. The trained BP neural network was used to process the data we collected to predict the number of global IWTs in the next 5 years, obtaining the results shown in Figure 2.

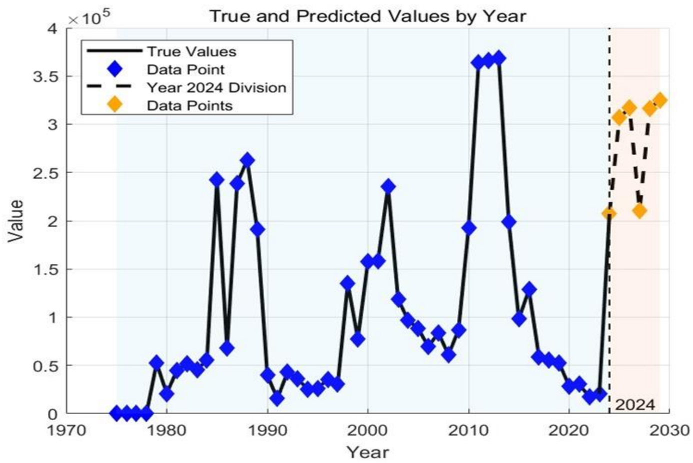

Figure 2. True and predicted values by year.

As can be seen in Figure 2, the trend of our forecast data for the next five years is roughly the same as the trend of the historical data, showing similar fluctuations. The fact that our forecast data show a similar pattern of fluctuations means that we have taken these influencing factors into account in our model and have made a reasonable forecast. Although some uncertainty remains, our overall forecasts for global instream wildlife populations over the next five years are robust. This fit with historical trends in the model suggests that our use of a BP neural network to train and predict IWT populations over the next five years is reasonably reliable.

The combination of historical data and BP neural network predictions suggests that, in the absence of major interventions, the global IWT population is expected to remain at a relatively high level for the next five years. This prediction is critical as it provides a clear goal and direction for our efforts. If IWT is left undisturbed, global IWT numbers will remain at a relatively high level for the next five years. Therefore, it is essential to implement our projects and to reduce or stop global IWT by taking relevant measures.

3.2. Optimal solutions for global conservation of wildlife preaching

The simulated annealing algorithm ensures that the routes of our campaign against illegal wildlife trade are optimized to minimize the time required for the International Public Interest Organisation's (INO) global campaigns, and thus increase the efficiency of the campaigns. Figure 3 below illustrates the results of our calculations, showing the optimal path from our TSP through the simulated annealing algorithm.

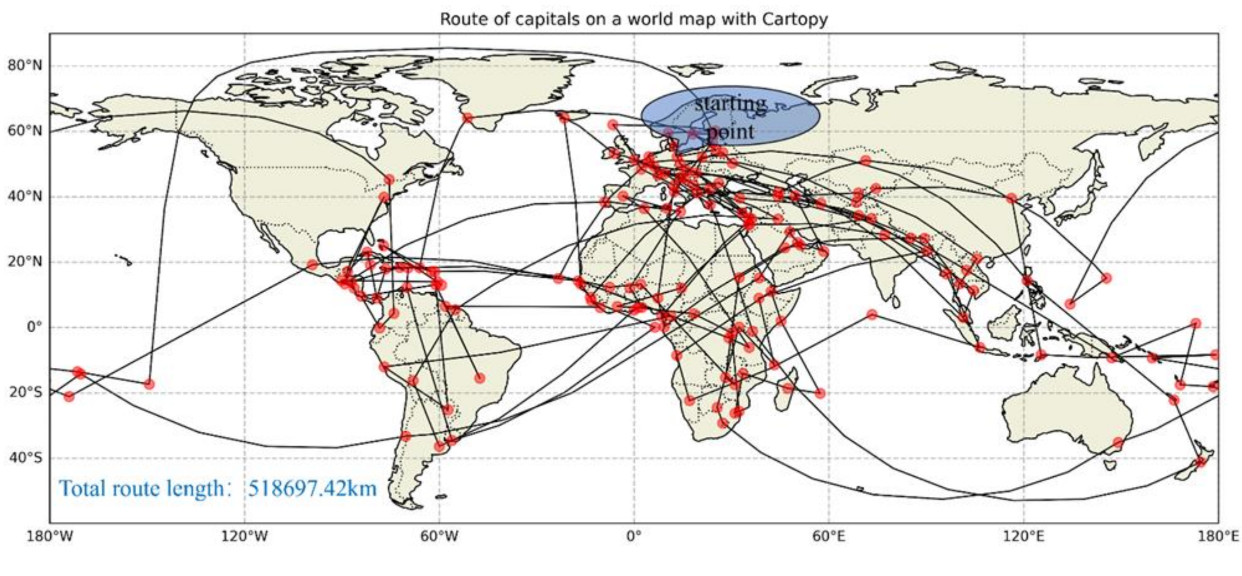

Figure 3. Optimal publicity route.

Therefore, based on the sum of the global advocacy paths, we can calculate that the minimum time for INO to complete the global advocacy cycle is about 1,696 days. What we need to measure is the change in people's support for fighting IWT during the advocacy period. Since advocacy activities are positively correlated with people's support, it can be hypothesized that advocacy activities can directly contribute to the increase in support and thus indirectly inhibit poaching. According to a survey conducted by the School of Life Sciences of Peking University, Biodiversity Science: Public Perceptions of Wildlife Consumption and Trade during Epidemics [10] people expressed a favorable response to the publicity campaigns on the attitude of illegal animal trade.

Table 1. Support for opposition to IWT.

	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Proportion	87.0%	8.1%	2.5%	1.3%	1.1%

Based on the statistical results of Table 1, the relationship between our advocacy process and people's support is satisfied.

$$Growth\ rate\ of\ \ people's\ support = 0.9568 \cdot Promotional\ activities\ progress \tag{17}$$

From equation (17), the deeper the sensitization process, the higher the level of people's support and the higher the level of support INO receives.

3.3. Establishment planning of monitoring facilities by greedy strategy

We identified five countries to establish monitoring regions, namely South Africa, China, United States of America, Swiss Confederation and Brunei Darussalam. Specific monitoring is shown in Figure 4:

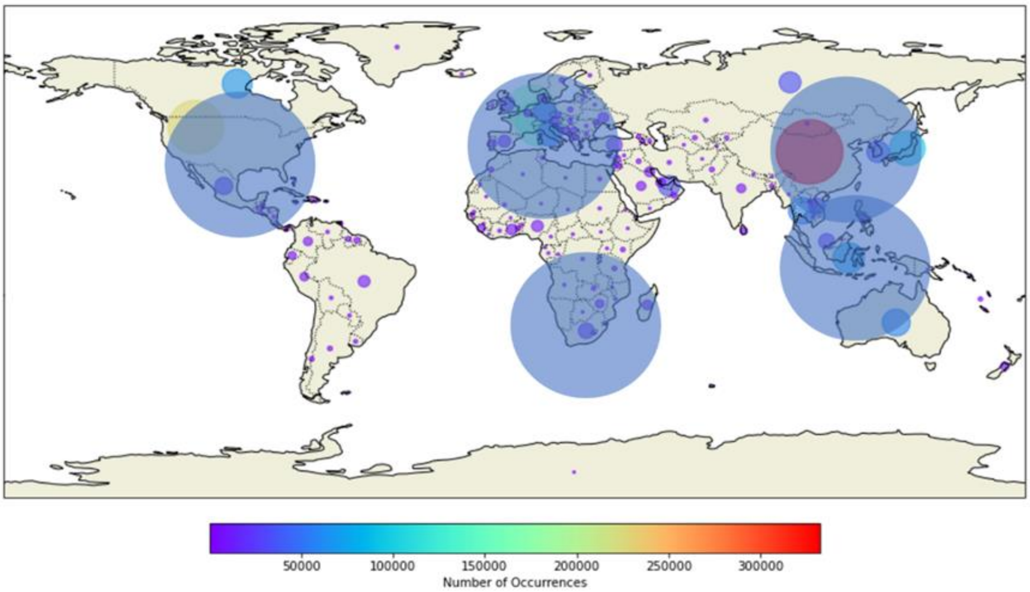

Figure 4. The location of monitoring systems.

Specific reasons for considering the establishment of these monitoring sites:

1. Switzerland: Located in the western part of Europe, the country has a well-developed maritime industry and maintains very close trade relations with foreign countries, which in turn leads to trade in some animal products.
2. China: China has a rapidly growing economy and a highly developed trade industry, and maintains trade with the rest of the world, and wildlife products may be found and traded in this neighborhood.
3. The United States of America: a developed country that maintains a high level of trade with the globe, while there is some demand for wildlife products in this country and there is often a remittance of wildlife products.

4. Brunei Darussalam: close to the equator, there exists a large amount of tropical rainforests, so there is a large number of wild animals, and there are illegal behaviors such as poaching in the area, and there is a large amount of wildlife outflow.

5. South Africa: the country itself has a large number of wild animals, and there is poaching behavior; at the same time, there is a certain demand for wildlife products, so there is relevant trade behavior with the neighborhood.

4. Conclusions and outlooks

Combating IWT is necessary, but the existing methods have proved to be insufficient to cope with the complexity as well as the large scale of IWT. Therefore, we collected data on IWT over the years and used a BP neural network to predict the number of IWT in the coming years, which showed that without major interventions, the number of IWT is expected to remain at a high level for the next five years. In addition, the TSP was used to optimize the global campaigning route for the campaign against IWT, and the results showed that the deeper the campaigning process was, the more support there was for the campaign, and the more support INO received. Finally, we used a greedy strategy to develop monitoring regions, considering some factors such as transport, climate, economy, etc., we decided to establish monitoring regions in five countries: South Africa, China, United States of America, Swiss Confederation and Brunei Darussalam. Thus, our approach is of great use in combating IWT.

At the same time, we hope to integrate more real-time data to continuously improve our model. International cooperation and information sharing are also important in combating IWT, and only through global cross-border efforts can we better combat IWT and protect global biodiversity.

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