ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on the Construction and Application of Knowledge Graph for Bird-Line Conflict Prevention and Management

Yong Liu[1,*], *Yang Tang*[1], *Jingdu Liu*[1] *and Guocai Li*[2]

[1] State Grid Aba Power Supply Company, Aba, Sichuan, 623200, China
[2] College of Electrical Engineering, Sichuan University, Chengdu, Sichuan, 610065, China

SUMMARY: *Bird line conflict is closely connected with power grid lines and bird activity habits, and its prevention and control work need to fully consider the construction of power system and bird protection. In this paper, based on the characteristics of bird line conflict research language, the conflict relationship between bird behavior and power line construction as the core content of its prevention and control knowledge map, using the maximum entropy model to train classifiers, to assist in entity relationship extraction under the perspective of the classifier. The knowledge representation learning model is used to complement the knowledge elements in the knowledge map, and the TransE, TransH and TransD models are selected to enhance the entity and relationship representation learning of the knowledge representation learning model from the spatial transformation level, and the ProjE and PTransE models are used to enhance the relationship feature representation ability of the knowledge representation learning model in the form of combining relationship vectors. Through entity-relationship extraction and knowledge representation complementation, this paper constructs a knowledge graph containing 7023 entity nodes, 4526 attribute nodes, and 7381 entity-attribute relationships for birdline conflict prevention and control. The knowledge graph can clearly show the types of bird line conflicts, bird species related to the conflicts, the contents of conflict prevention measures and the correspondence between them, which provides a reliable path reference for bird line conflict prevention.*

KEYWORDS: *entity-relationship extraction; knowledge graph complementation; knowledge representation learning; birdline conflict control*

1 Introduction

With the continuous progress and development of society, the current social production and life of the demand for electric energy continues to increase, promoting the development of the power industry. In the power system, transmission line is one of the important components, is to ensure the safe and smooth operation of the power system based on, however, in the transmission line there are often birds stay on it, as well as bird droppings and other objects will affect the normal operation of the transmission line, but also lead to the birds are hurt [1-3].

The traditional measures to prevent and control the conflict between birds and lines include installing new bird spikes to inhibit birds from resting and nesting in the lines, installing ultrasonic bird repellers to repel birds by sound waves, and installing large-diameter aerodynamic insulators, etc. [4-6]. However, the main problem of these prevention and

*ab_ly0014a@163.com
https://doi.org/10.65102/is2026521
Published: 30 April, 2026

control measures is that they need to be installed manually, which is not only costly, risky, and inefficient, but also unable to meet the needs of the current rapid development of the power system. With the development of artificial intelligence and the application of smart grid, the great advantage of knowledge graph in bird line conflict prevention and control has received wide attention.

A knowledge graph is a network that organizes the knowledge of "entity-attribute relationships" in a specific domain in a form that can be queried and reasoned about [7]. It is not just a collection of data, but a "semantic map" that allows different data sources to interface with each other and be understood by both machines and humans. In practice, the goal of knowledge mapping is often to integrate scattered and heterogeneous facts to form a unified cognitive portal, which helps to improve the efficiency of retrieval, analysis, reasoning and decision-making [8, 9]. Regarding the research on knowledge graphs and their related applications, literature [10] specifies that human knowledge is a structured understanding of the world, and knowledge graphs have become an important research direction in cognition and human-like intelligence by characterizing the relationships among entities, and reviews its four major areas, namely representation learning, knowledge acquisition and complementation, time-series knowledge graphs, and knowledge-aware applications. Literature [11] reveals that with the development of artificial intelligence and big data, knowledge graphs, as a structured tool for effectively organizing and presenting massive knowledge, have received extensive attention from academia and industry, and systematically outlines its opportunities and challenges, with a view to providing insights for future research. Literature [12] argues that with the explosive growth of data, it becomes more and more difficult to efficiently acquire knowledge from the huge amount of information, and knowledge graphs provide a universal representation framework for this purpose, and systematically reviews the types of knowledge graphs, construction methods and existing systems. In the prevention and control of bird line conflicts, the construction of knowledge graphs can effectively build a semantic network containing transmission lines, bird distribution, and conflict events, so as to realize the intelligent prediction and prevention of bird line conflicts.

Regarding the hazards of bird-line conflicts and the application of their prevention and control measures, the literature [13] emphasized that high-voltage transmission lines increase the mortality rate of bird collisions, and took Belgium as an example, based on the distribution data of birds, it proposed a high-resolution risk mapping method, screened the collision-prone species and constructed a spatial layer through the casualty records, and pointed out that the wetlands and the valley were the high-risk areas for collisions, and the map could identify the risks of new lines and optimize the existing lines for mitigation. The map can identify the risk of new routes and optimize existing routes for mitigation. Literature [14] pointed out that transmission line electrocution poses a serious threat to birds, especially endangered species, and the existing mitigation measures lack of prioritization, which may lead to resource mismatch. Therefore, a framework for identifying high-risk areas is proposed, and a risk map combining the range of species and the grid's hazardous surfaces is generated and validated, which emphasizes that the method is applicable to data-scarce areas and provides a basis for prospective strategies of energy companies. Taking South America as an example, literature [15] integrates data from scientific literature to point out the problems of many affected species, unknown geographic risk zones, and lack of evaluation of the effectiveness of mitigation measures in this region, and emphasizes the need to scientifically identify high-risk zones in order to avoid building new lines and retrofitting existing hazardous lines, as well as to promote the development of national regulations to mitigate the impacts on wildlife. Literature [16] emphasized the application of ultrasonic bird repellers in solving the problem of bird damage in electric power system, through the design of multi-area experiments and the use of behavioral analysis software, explored the mechanism of its impact on the behavior of pigeons, and found that there are differences in the individual response but the overall impact is significant, which provides a reference for scientific installation and application. Literature [17] pointed out that cranes are very easy to collide with high-voltage lines due to limited flight field of vision, of which 2774 accidents involving 14 species, the most effective measures for the line underground or bypass, the new line should be parallel to the existing facilities and low-hanging thick, but need to be verified, and emphasized that there is insufficient evidence of the effectiveness of the current “bird avoidance device”, and the dynamic device is slightly better. Literature [18] indicates that bird droppings across the gaps of live or grounded components can cause short circuits leading to power outages, therefore, through a literature review, effective mitigation measures for medium and high voltage lines such as bird repellents, shields, and tower modifications are analyzed, emphasizing the need for proper installation and maintenance of the equipment as well as the involvement of multiple stakeholders to ensure the long term effectiveness of the measures.

In this paper, combining the causes of birdline faults with the characteristics of existing bird conflict research, entity relationship extraction is carried out from the perspective of a classifier, and the maximum entropy model is used as the training method for the relationship extraction classifier. The corresponding entity relationship translation model is selected for different entity relationship nature translation needs in the knowledge graph, and the construction model of bird line conflict prevention and control knowledge graph is formed through the complementation of distributed vector representation of knowledge elements. Through several experiments, the feasibility of the entity relationship extraction method and knowledge graph complementation scheme designed in this paper is determined, and the knowledge graph of birdline conflict prevention is constructed and visualized.

2 Birdline Conflict Fault Types

The reasons for tripping of overhead power lines due to bird damage are broadly categorized as follows:

(1) When birds build nests on overhead power lines, they need to use some branches, wire, gold foil and other materials. In its grips in the air when flying, the object will occasionally fall off the condition, such as when it falls between the wire and the cross-support, will instantly lead to a short circuit. This type of failure occurs at a high rate, the failure point is not conducive to finding.

(2) In cloudy weather conditions, often accompanied by gusts of wind and heavy rain, the nest on the tower is wet or blown off by the wind, such as its fall on the wire or hanging bottle, can cause a short circuit of the transmission line grounding fault. The frequency of this type of fault is very low, but the fault point is not easy to find.

(3) birds in the cross or conductor flying over the defecation, bird droppings with the wind blowing to the charged conductor caused by the breakdown of the air gap, thus causing the fault. This type of accident occurs in windy weather, and more for the defecation of large birds, this fault is more common, and very easy to find.

(4) Birds are often active between the cross-arms, the amount of defecation is also very small, will not produce a direct burden on the line. But with the accumulation of time, the impurities on the cross-trunk thickening, after the rain, windy weather can be tripped. This kind of fault belongs to the special dirt flash.

(5) Some birds, such as crows, etc. happy to mouth branches, wire and other flight, in the

conductor or over the shuttle flight, easy to lead to grounded short circuit or phase to phase short circuit.

(6) Birds in the conductor to eat food, easy to cause line ground tripping. Overhead power lines after the occurrence of bird tripping faults will cause some interference to the safety of the grid operation, but the basic performance of the reclosing gate is still intact, will not cause large-scale accidents. But it is when there are problems with circuit breakers or protection secondary equipment that the situation is amplified.

3 Modeling the Knowledge Graph for Birdline Conflict Prevention and Control

3.1 Entity relationship extraction

3.1.1 Description of tasks

As a complex project involving the construction of power lines and the survival of birds, bird line conflict prevention and control, its related research often has a formal language style, a single syntactic structure, and expresses a direct and clear semantic relationship, and many sentences expressing the same semantic relationship have a high degree of similarity in structure. Therefore, in this paper, for these features of the research data, entity-relationship extraction is carried out from the perspective of training classifiers, and the specific tasks are described as follows:

Entity-Relationship Extraction Given a sentence $s = < w_1, w_2, ..., e_1, w_i, w_j, e_2, w_k, ..., w_n >$ and relationship R containing two entities e_1 and e_2, the task of relationship extraction is to learn a binary classifier as in equation (1):

$$f(s) = \begin{cases} 1, & if\ e_1\ and\ e_2\ satisfy\ the\ relation\ R \\ 0, & otherwise \end{cases} \quad (1)$$

Before training the classifier, there are two preparations that need to be done in advance: (1) determining the semantic relations to be extracted and the set of verbs that can describe the semantic relations; and (2) determining the constraints of each keyword on the relative order in which the entities appear in the sentence.

There is a big difference between relationship extraction in the vertical domain and relationship extraction in the open domain, mainly because it is usually difficult to determine what kind of words can express what kind of semantic relationships in what kind of contexts when extracting entity relationships in the open domain, whereas in the vertical domain knowledge graph, since the relationships between entities to be extracted are usually very clear, the verbs that are able to express the semantic relationships are also very clear, very limited, thus making it possible to manually determine all the verbs that describe a given semantic relationship. In this paper, we use the MapReduce program to count the word frequencies of all verbs in the research data, and then summarize the target relations and the set of verbs corresponding to the relations extracted in this paper based on the word frequencies. In the process of counting word frequencies, this paper first merges two consecutive verbs in a sentence into one verb, and then counts the word frequencies of the merged verb. The advantage of doing so is that when two verbs are merged into one verb, the semantic relation expressed by that verb is more complete.

After determining the semantic relations to be extracted and the set of verbs, since each verb restricts the order of appearance of the entity in the context, this paper defines each verb that has a constraint on the order of appearance of the entity. Defining the restriction conditions of verbs has the following two advantages: (1) pairs of entities that do not satisfy the restriction conditions can be filtered in advance, which accelerates the speed of the system in processing the data; (2) for the two entities that satisfy the semantic relationship, they can be output as a ternary or a multivariate group according to the restriction conditions of the verbs on them in order.

3.1.2 Relationship classification based on maximum entropy modeling

In this paper, the maximum entropy model is chosen to train the classifier for relational extraction with the following three considerations:

(1) The maximum entropy model expresses features through feature functions, so it can easily define complex features in natural language, and it is easy to adjust the fit of the model to the training data by simply modifying the feature functions;

(2) The maximum entropy model only makes assumptions on the given feature functions, and assumes that the other unknown features are uniformly distributed, which is a good solution to the common parameter smoothing problem in natural language processing;

(3) The maximum entropy model makes the model highly interpretable by solving for the weights corresponding to each feature. The above three advantages are difficult to be reflected in other machine learning models, for example, the plain Bayesian model assumes that the features are independent of each other in order to reduce the number of parameter estimation, whereas in natural language, words have strong correlation with each other, and it is unreasonable to assume that they are independent of each other. In addition, although Support Vector Machines (SVMs) can also achieve good results in binary classification problems, the interpretability of SVMs is poor.

The main idea of the maximum entropy model is: consider a stochastic process affected by contextual information $x \in \mathcal{X}$ produces an output state $y \in \mathcal{Y}$, where $\mathcal{X}$ is a finite set of contextual information, $\mathcal{Y}$ is a finite set of output states, and based on the stochastic process' Based on the historical data of the stochastic process, the empirical distribution of y under the given contextual information x can be counted, i.e., $\hat{p}(y \mid x)$, and the maximum entropy model models $p(y \mid x)$ such that $p(y \mid x)$ approximates this empirical distribution $\hat{p}(y \mid x)$ with the maximum probability.

The maximum entropy model uses the characteristic function $f(x, y)$ to express the correlation between the input information x and the output state y as in equation (2):

$$f(x, y) = \begin{cases} 1, \textit{if } \; x \textit{ and } y \textit{ satisfy some condition} \\ 0, \textit{otherwise} \end{cases} \tag{2}$$

The feature function is usually a 2-valued function that takes 1 when a fact is satisfied between the input feature x and the output state y, otherwise it takes 0. In natural language processing, complex features of the context can be expressed very flexibly by defining the feature function. For example, in the process of extracting the relationship of “bird damage”, a feature of a positive case is observed: the keyword “obstacle” is located between two entities, then this feature can be expressed by a feature function as in equation (3):

$$f(x,y)=\begin{cases}1, if\ \ y=1\&\&\ the\ keyword' \\ acquisition' is located between two entities \\ 0, otherwise\end{cases} \tag{3}$$

After defining the feature function, in order to make the model $p(y|x)$ approximate the empirical distribution $\hat{p}(y|x)$, the maximum entropy model constrains the expected value of the feature function about $p(x,y)$ and the expected value about the empirical distribution $\hat{p}(y|x)$ to be equal to ensure that the model constrains the existing information. There are many or even infinite models that satisfy this constraint, and the maximum entropy model is the model with the largest information entropy in the set of models that satisfy the constraint, which is formally defined in equation (4):

$$\begin{gathered}\max_p H(p)=-\sum_{x,y}\tilde{p}(x)p(y|x)\log p(y|x) \\ s.t. E_{\tilde{p}}<f_i>=E_p<f_i>, i=1,2,3,\cdots,n \\ \sum_y p(y|x)=1\end{gathered} \tag{4}$$

The maximum entropy model expression (5) is then obtained by optimizing Eq. (4) through the Lagrangian pairwise optimization:

$$p(y|x)=\frac{1}{Z(x)}\exp\left[\sum_{i=1}^{n}\lambda_i f_i(x,y)\right] \tag{5}$$

where $Z(x)$ is the normalization factor, $f_i(x,y)$ represents the ith eigenfunction, and λ_i represents the weights of the ith eigenfunction, which is also the parameter that the model eventually learns.

3.2 Knowledge Graph Completion Based on Knowledge Representation Learning Models

Knowledge graph completion methods based on knowledge representation learning techniques to obtain distributed vector representations of knowledge elements in a knowledge graph have become a mainstream research in academia and are widely used in knowledge graph completion tasks. These methods learn the low-dimensional distributed representations of knowledge elements such as entities or relations in the knowledge graph triad, so as to represent or store the knowledge elements in the form of vectors, which are very convenient for processing and utilizing the intrinsic semantics of knowledge entities and relations using mathematical tools. The knowledge representation learning method based on translation model has become the mainstream of knowledge representation learning method due to its simple and efficient features, and it is the important foundation and technical means for the current knowledge graph complementation task.

The TransE model is the first translation model. This model models the relationship between entities within the triples of the knowledge graph in the vector space as a translation operation from the head entity to the tail entity. That is, it is assumed that the vector t corresponding to the tail entity t in the triple $T=<h,r,t>$ is translated from the vector h corresponding to the head entity h along the vector r corresponding to the relation r.

The TransE model mainly examines the L_n distance between $h+r$ and t, and its basic starting point is to minimize the L_n distance between $h+r$ and t (usually considering L_1 or L_2 distance). Based on this goal, TransE defines the scoring function shown in Formula (6), and based on this scoring function, it defines the loss function shown in Formula (7).

$$f_r\left(h,t\right)=\left\|h+r-t\right\|_{L1/L2} \tag{6}$$

$$L=\sum_{<h,r,t>\in G}\sum_{<h',r,t'>\notin G}\left[\gamma+f_r(h,t)-f_r(h',t')\right] \tag{7}$$

In Equation (7), $<h,r,t>$ denotes the existing ternary in the knowledge graph corresponding to the real established ternary in the real world, which is usually also called the golden ternary, and is generally treated as a positive example during the training process; while $<h',r,t'>$ denotes the ternary that doesn't exist in the knowledge graph, which is also called the damaged ternary, and is generally treated as a negative example during the training process; and γ is the the minimum discriminative distance between the golden ternary and the damaged ternary.TransE model is a kind of knowledge representation learning model with simple structure and fewer network parameters, which has low computational complexity and is more suitable for large-scale knowledge graph complementation tasks. However, the TransE model has a natural drawback, as the model measures the relationship between head and tail entities in a simple low-dimensional space, which results in this model only being able to effectively characterize one-to-one simple entity relationships.

However, in the real world, usually an entity not only corresponds to only one other entity, but also has complex relationships such as one-to-many, many-to-one and many-to-many. To represent these complex entity relationships, this paper adopts a translation model based on spatial projection, called TransH. The TransH model projects the vectors corresponding to the head and tail entities onto a hyperplane in the vector space according to Eq. (8) and Eq. (9) to obtain new projection vectors, and then based on the projection vectors with Eq. (6) as the objective function for training, learns the normal vectors w. When there is more than one relationship between two entities, these two entities can be projected to different hyperplanes for calculation.This treatment of TransH model is relatively simple, but it solves the problem that TransE model can only deal with one-to-one simple relationship to a certain extent, and obtains a good effect in the dataset where there are complex relationships. However, this model still models the semantic relationships between entities in the same semantic space, which limits the representation ability of this model to some extent, so there is still room for improvement.

$$h'=h-w^T hw \tag{8}$$

$$t'=t-w^T tw \tag{9}$$

There is also a principle of TransR model that separates the entity space from the relation space as in Fig. 1. This model projects the head and tail entities in the entity space to the relation space through an identical projection matrix, and then computes the L_n distance between the projection vectors of the head entity translated to the tail entity vectors through the relation in the relation space. This model allows entities that are close in the original solid space to be effectively separated after projection into the relational space, and therefore has better representation learning capability.

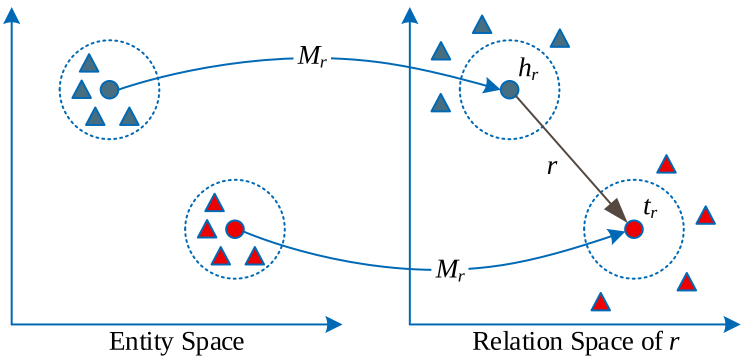


Figure 1: The principle of the TransR model

In addition to enhancing the model's ability to learn entity and relation representations in terms of spatial transformations, etc., some of the work focuses on some of the properties possessed by the entities or relations themselves. Unlike other translation models, the ProjE model views the knowledge graph completion problem as a candidate ranking problem, and its model architecture is shown in Fig. 2.ProjE is an artificial neural network model that contains a combinatorial layer and a projection layer.

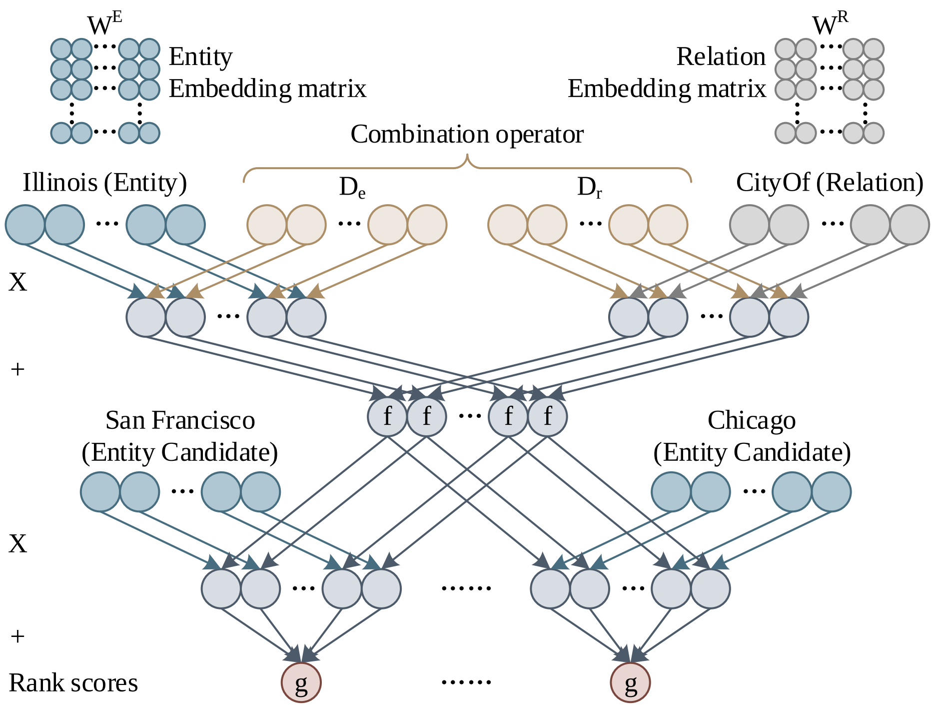


Figure 2: The ProjE model architecture

In the combination layer, the entity vector and the relation vector are respectively combined into the target vector through a diagonal matrix called the combination operator according to formula (10), where e and r represent the entity vector and the relation vector respectively, D_* is the diagonal matrix, and b_c is the bias vector. After being combined into the target vector, it is projected into the candidate entity space according to formula (11), where W^c represents the matrix composed of the candidate entity vectors, and b_p represents the corresponding bias vector. This way, the scores of e and r on each candidate entity can be obtained. The ProjE model improves the model performance by optimizing the collective ranking loss of the candidate entity (or relation) list. This approach has stronger representation learning ability compared to previous translation models. The ProjE model effectively reduces the model complexity on the basis of improving the representation learning ability, and does not require complex preprocessing of the dataset. It is a typical end-to-end knowledge representation learning model. In addition, the ProjE model proposes to use negative sampling to create a smaller training dataset, which effectively reduces the additional computational cost caused by too many negative examples while ensuring the learning performance.

$$f(e,r) = \tan(e \oplus r) = \tanh(D_e e + D_r r + b_c) \tag{10}$$

$$h(e,r) = \tanh\left(W^c f(e,r) + b_p\right) \tag{11}$$

In addition to having direct relationships between entities in the knowledge graph, they also contain many indirect relationships, which also play an important role in the knowledge graph complementation task. In order to learn the feature representation of the indirect relationships between entities in the knowledge graph, this paper adopts a PTransE model, whose architecture is shown in Fig. 3.The PTransE model constructs the indirect relationships between entities into a new relationship by combining them in a combinatorial way, and regards this new relationship as the translation vector between the starting entity vector and the final entity vector.Indirect Relationships Adopted by the PTransE Model The combination methods include vector summation, vector cumulative multiplication and recurrent neural network, etc., among which the combination method of vector summation achieves the best results.The RTransE model also takes into account the existence of indirect relationships between entities and takes minimizing the overall distance on the path of entities with connections as the optimization objective. These path-based translation models consider both the direct relationship path information and the indirect relationship path information existing between entities in a comprehensive manner, which further improves the knowledge representation learning model's complementation ability on the knowledge graph complementation task. However, in these models, too long paths bring problems such as parameter explosion, and not all entity-relationship paths are reliable, so these models usually only consider indirect entity-relationship paths with a length of about 2 or 3, and there is still room for improvement.

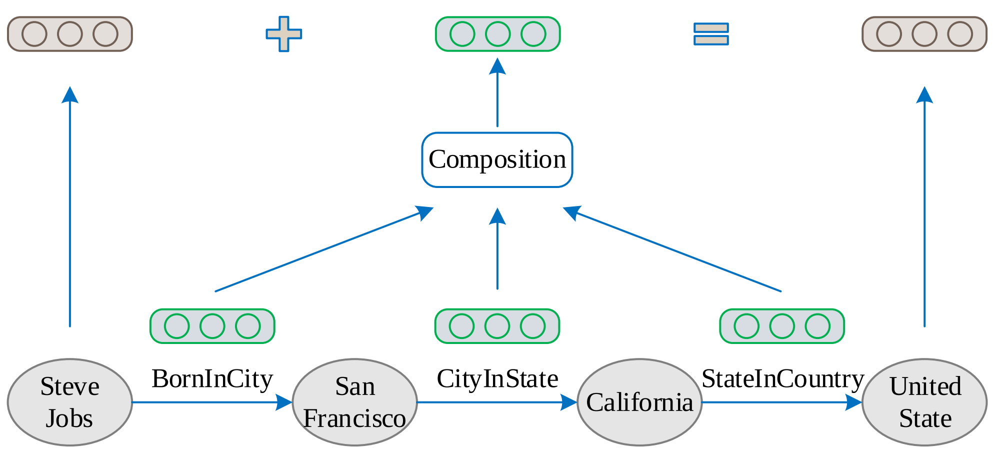


Figure 3: The PTransE model architecture

4 Construction and Visualization of Birdline Knowledge Graph Prevention and Control

4.1 Named Entity Recognition Experiment

4.1.1 Bird entity recognition effects

Taking bird entity recognition as the main task of named entity recognition, the entity categories it needs to acquire are mainly related bird species in bird line conflicts. During the experimental training process, 2378 pictures of different bird line conflicts were collected in the field and online, and 326 extraction rules were constructed based on the picture data. Under these conditions, multiple sets of experiments were conducted for different bird species and bird orders in bird line conflicts.

According to the wintering place and breeding place, the birds are divided into five types: resident birds, summer migratory birds, winter migratory birds, travelling birds and lost birds, and after collecting certain test corpus for the five types of birds to start the closed test, the method of this paper is used to carry out the recognition experiments, and the statistical results of the experimental results are shown in Table 1.The recognition accuracy of this paper's method for the five types of birds is over 90.00%, and the average recognition accuracy is as high as 97.40%, the average recall is 89.13%, and the overall recognition accuracy is more than 90%, and the average recognition accuracy is as high as 97.40%. 89.13%, the overall recognition performance is good.

Table 1: The classification test results of five types of birds

	Total	Identify quantity	Correct quantity	Incorrect quantity	Recall Rate	Accuracy Rate
Resident birds	53	50	49	1	83.28%	98.00%
Summer migratory birds	35	34	34	0	87.52%	100.00%
Winter migratory birds	36	32	30	2	94.65%	93.75%
Traveling birds	65	59	57	2	90.36%	96.61%
Lost birds	74	73	72	1	89.85%	98.63%
Total	263	248	242	6	89.13%	97.40%

The results of further categorization and identification tests of related bird species in the bird line conflict are shown in Table 2, and its related bird species mainly contain 5 orders of storks, falcons, owls, finches, and geese. The average accuracy of recognizing bird species related to the bird line conflict is 97.62%, and the accuracy of recognizing owl-shaped birds is as high as 100.00%, with an average recall rate of 87.20%. It shows that the method can recognize bird species with potential impact on power lines more accurately, providing solid technical support for the prevention and control of bird-wire conflicts.

Table 2: Identification of bird species related to bird line conflicts

	Total	Identify quantity	Correct quantity	Incorrect quantity	Recall Rate	Accuracy Rate
Ciconiformes	86	82	80	2	88.00%	97.56%
Falconiformes	35	30	29	1	89.00%	96.67%
Kakiformes	36	31	31	0	93.00%	100.00%
Passeriformes	65	60	58	2	81.00%	96.67%
Anseriformes	74	71	69	2	85.00%	97.18%
Total	296	274	267	7	87.20%	97.62%

4.1.2 Analysis of relationship extraction results

The following three relationship extraction methods are selected as controls: feature vector-based relationship extraction (REFC), traditional sequence kernel relationship extraction (TSKE), and semantic sequence kernel extraction (SSKE), and the common outputs of the relationship extraction for bird species and bird orders (S-O), bird orders and bird damage types (O-D), bird damage types and control measures (D-C), bird line conflict system (BLS), bird damage control system (BCS) are shown in Table 3.From an overall perspective, the relationship extraction effect of this paper's method for the five system relationships is better, and its accuracy, recall and system performance are all concentrated in Table 3.From the overall point of view, the accuracy, recall and system performance of this paper's method are all concentrated in Table 3. system (BCS) are shown in Table 3.From an overall perspective, the method in this paper is more effective in extracting the relationships of the five systems, and its accuracy, recall and system performance are all concentrated in the interval of (79.00,90.00)%, which is superior and more stable. In terms of specific categories, the method in this paper is not very good at extracting relationships of bird line conflict system (BLS), and its accuracy, recall and system performance are not optimal within the category, while it is more effective in extracting relationships of bird line conflict related bird species and bird order (S-O) and bird pest control system (BCS), and all three indicators are optimal among the four methods.

Table 3: Relationship extraction results (%)

		REFC	TSKE	SSKE	Textual
S-O	Precision	86.09	83.42	81.07	**87.54**
	Recall	73.34	74.17	76.04	**89.51**
	F1	81.12	78.15	77.73	79.35
O-D	Precision	77.65	77.27	75.67	**87.47**
	Recall	70.63	71.83	73.4	**83.25**
	F1	74.19	75.7	70.77	**81.42**
D-C	Precision	81.03	85.78	81.85	84.99
	Recall	86.95	85.15	81.02	79.52
	F1	80.36	83.74	80.82	**87.93**
BLS	Precision	77.23	75.01	79.61	79.11
	Recall	86.07	85.98	84.87	82.84
	F1	82.85	81.93	87.64	82.32
BCS	Precision	78.51	80.43	76.69	**83.09**
	Recall	73.46	75.33	75.27	**82.97**
	F1	79.04	83.14	87.81	**89.12**

4.2 Evaluation of Knowledge Graph Construction Models

4.2.1 Ternary classification effects

The bird hazard prevention database was selected as the source of knowledge graph data required for model training. After removing irrelevant information, 26,341 entities were separated and designated as out-of-kb entities. Then, all triples involving out-of-kb entities were classified into 4 categories: those without out-of-kb entities (e-e), where the subject is out-of-kb but the object is not (w-e), where the object is out-of-kb but the subject is not (e-w), and where both entities are out-of-kb (w-w). Taking the entity name-based alignment method (name), entity link-based alignment method (links), and entity description-based alignment method (descriptions) as the control, the output of the correctness rate of the four modeling methods on the four types of triples is shown in Table 4. The correctness rate of this paper's model on the four types of triples, e-e, w-e, e-w, and w-w, is in the order of 89.32%, 87.45%, 78.85% and 86.60%, which is stable above 78.00%, and is the best performance among the four modeling methods in the three types of ternary groups of e-e, w-e and w-w. Compared with the three control models, the model in this paper has the strengths of superior performance and stability in ternary group classification.

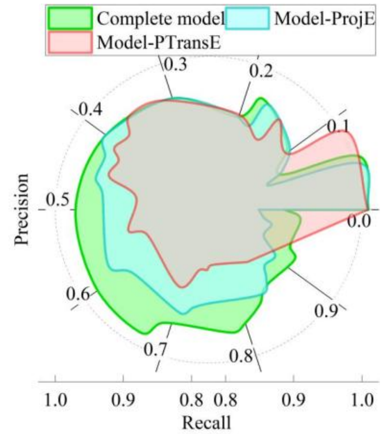
Table 4: The triplet accuracy of different models

Type	name	descriptions	links	Textual
e-e	84.54	72.53	80.34	89.32
w-e	72.31	66.43	79.72	87.45
e-w	80.81	88.3	85.17	78.85
w-w	77.06	82.03	73.43	86.60
All	81.86	69.3	76.69	81.91

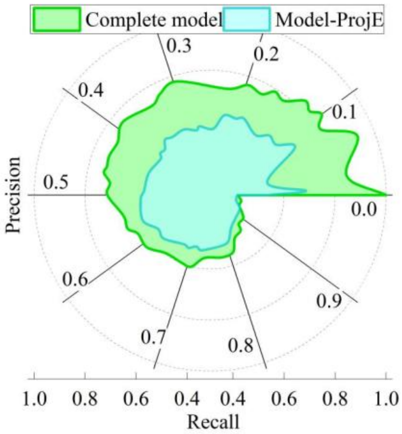
4.2.2 Validation of the complementary effect of knowledge mapping

As can be seen from Section III, after completing the basic construction of the knowledge graph for birdline conflict prevention and control through entity relationship extraction, this paper also designs the knowledge graph complementation work based on the knowledge representation learning model. In this complementation work scheme, TransE model, TransH model and TransD model are the translation models of entity relations under the perspective of spatial transformation.ProjE model and PTransE model are the feature representation models of entity direct and indirect relation vectors by combining vectors, respectively.

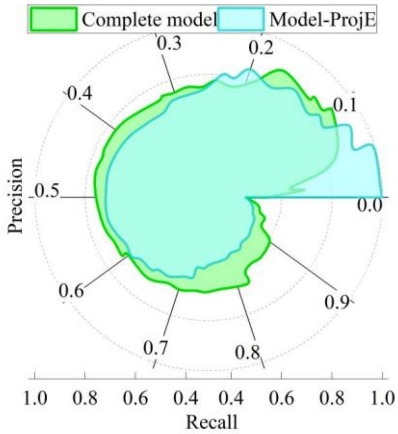
In order to verify the effect of the knowledge graph complementation scheme, this section carries out the knowledge graph construction model after excluding the feature representation models ProjE and PTransE, and the comparison of the PR curve representation with the complete model in the four sets of ternary group relations is shown in Fig. 4(a)-(e). In addition, the commonly used multi-view knowledge representation learning model (SMGNN) is selected for the comparison of ternary group recognition effect before and after adding ProjE model with PTransE model module is shown in Fig. 5(a)-(e). Comprehensively observing Fig. 4 and Fig. 5, the PR curve area of the complete knowledge representation learning model in this paper is larger than that of the PR curve area after excluding the ProjE model/PTransE model, i.e., the knowledge graph construction model under the complete knowledge graph supplementation scheme has a more superior ternary group classification capability. Similar to the performance of the knowledge graph construction model in this paper, the SMGNN model with the addition of the ProjE and PTransE translation models has significantly enhanced its ability to extract and classify the ternary relationships in “e-e”, “w-e”, “e-w”, and overall relations, with recalls of 0.600 and above.



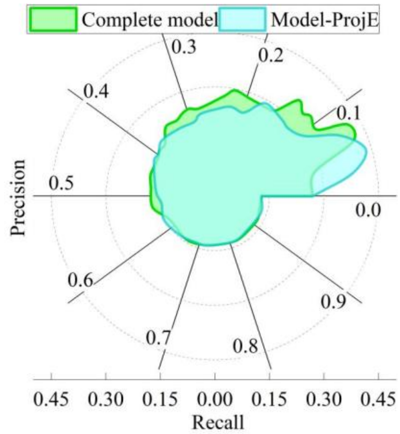
(a) e-e



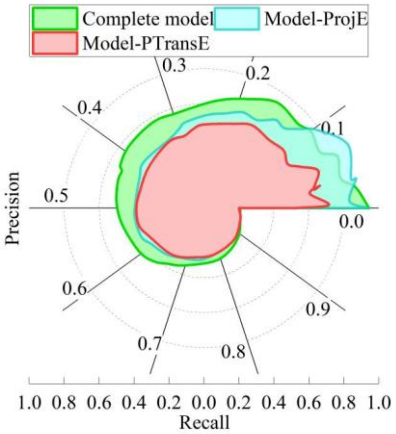
(b) w-e



(c) e-w

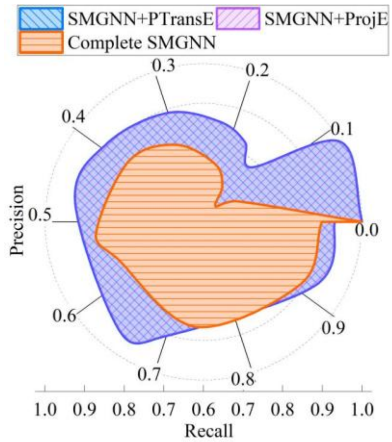


(d) w-w

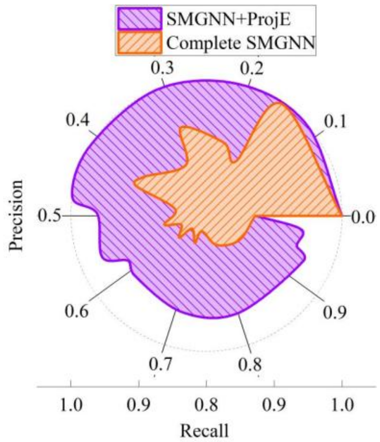


(e) All

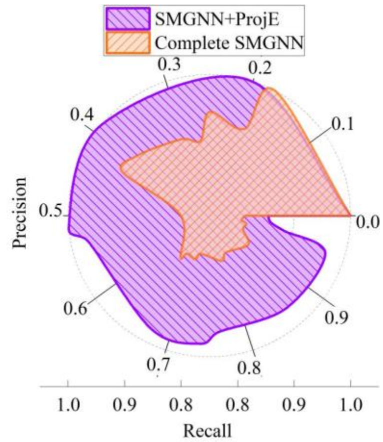
Figure 4: The precision and recall curves of the complete model and the partial model



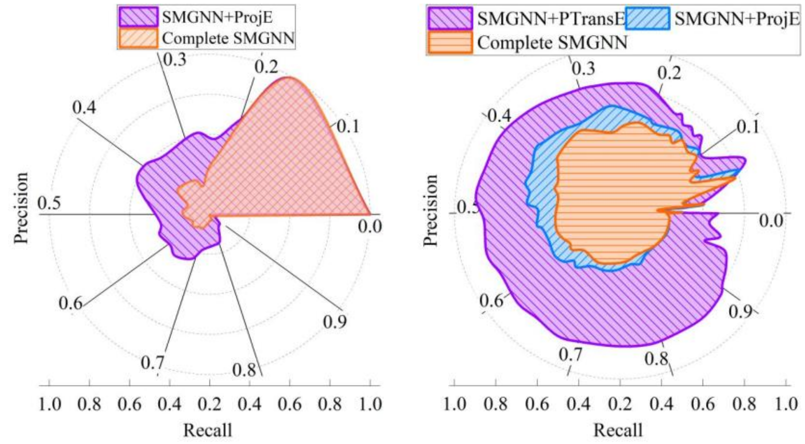
(a) e-e



(b) w-e



(c) e-w



(d) w-w (e) All

Figure 5: The precision and recall curves before and after adding the model

4.3 Visualization of the Knowledge Graph for Birdline Conflict Prevention and Control

The model proposed in this paper is used to construct a knowledge graph for bird line conflict prevention and control, which contains a total of 7023 entity nodes, 4526 attribute nodes, and a total of 7381 relationships between entities and attributes. The visualization of the bird line conflict bird species, types and control measures is shown in Figure 6.The main types of bird line conflict are 3 types: nesting, excretion and flight conflict faults, of which the nesting bird species to the storks, falcons, and owls are the main three types, 5 types of birds have excretion behavior, due to flight conflict faults to the storks, owls, and two types of large birds are the main ones. For the excretion and flight failure caused by the bird line conflict, prevention and control measures to repel birds, can be used to place the bird baffle, placed bird repeller, coated with anti-bird magnetic paint, placed anti-bird spikes, placed anti-bird box and other measures. For the bird line conflict caused by nesting behavior of birds, it can be guided away from power lines by building nests to avoid bird line conflict.

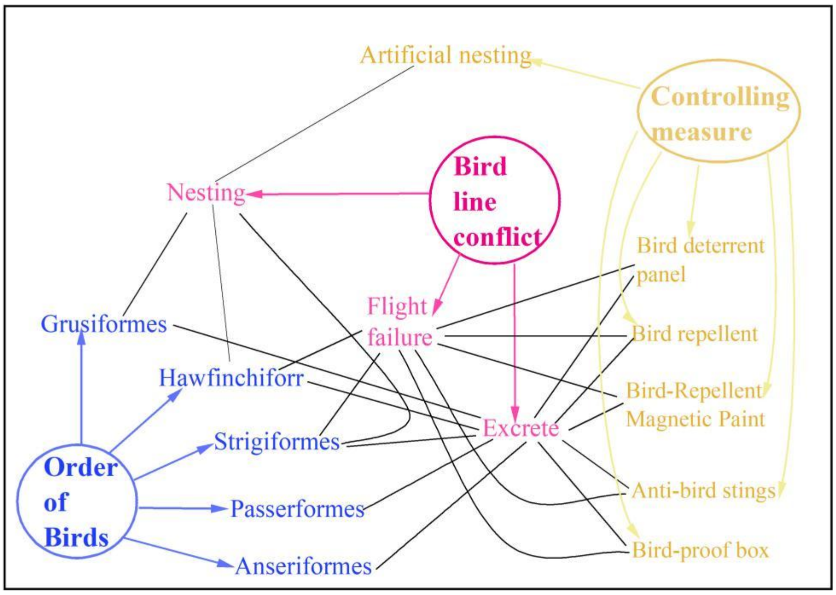


Figure 6: Knowledge Graph of bird-line conflict Types and Prevention measures

5 Conclusion

In this paper, we designed a relationship extraction method for bird line conflict prevention and control entities under the perspective of classifier, and its classifier was trained by the maximum entropy model, which was able to recognize the relevant bird species in the bird line conflict with an average accuracy of 97.62% and an average recall of 87.20%, and for the main five kinds of relationships in the bird line conflict prevention and control system the accuracy, recall and system performance were concentrated in the interval of (79.00,90.00)%. Combined with the knowledge graph complementation scheme based on knowledge representation learning, the knowledge graph construction model formed is able to stabilize the classification accuracy above 78.00% for the 4 types of triads. Through entity relationship extraction and complementation, the knowledge graph established for bird line conflict prevention and control contains 7023 entity nodes and 4526 attribute nodes, with systematic relationship correspondence between bird line conflict types, related bird species and prevention measures, which can effectively improve the pertinence and effect of bird damage prevention and control on transmission lines.

Funding

This research was supported by the State Grid Sichuan Electric Power Company Science and Technology Project Funding: Research on Ecological Governance Technology of Bird-related Faults in Transmission Lines Based on Image Recognition: A "Combination of Prevention and Control" Approach (52191923001).

About the Author

Yong Liu, male, Han ethnicity, born in 1969, from Yilong, Sichuan Province, holds a bachelor's degree and is a professor-level senior engineer. His main research focuses on power grid operation and maintenance management, new energy technologies, and relay protection.

Tang Yang, male, Han ethnicity, born in 1991, from Langzhong, Sichuan Province, holds a bachelor's degree and is an engineer. His primary research focuses on power grid dispatching operations, data analysis, and applications.

Jingdu Liu, male, Han ethnicity, born in 1986, from Fengjie, Chongqing, holds a bachelor's degree and is a senior engineer. His primary research focuses on power grid operation and maintenance management, as well as relay protection.

Guocai Li, male, Han ethnicity, born in 1975, is a postgraduate and associate professor from Rong County, Sichuan Province. His primary research focuses on new energy technologies and knowledge graphs.

References

[1] Burdett, E. M., Muriel, R., Morandini, V., Kolnegari, M., & Ferrer, M. (2022). Power lines and birds: drivers of conflict-prone use of pylons by nesting white storks (Ciconia ciconia). Diversity, 14(11), 984.

[2] D’Amico, M., Catry, I., Martins, R. C., Ascensao, F., Barrientos, R., & Moreira, F. (2018). Bird on the wire: Landscape planning considering costs and benefits for bird populations coexisting with power lines. Ambio, 47(6), 650-656.

[3] Bernardino, J., Bevanger, K., Barrientos, R., Dwyer, J. F., Marques, A. T., Martins, R. C., ... & Moreira, F. (2018). Bird collisions with power lines: State of the art and priority areas for research. Biological Conservation, 222, 1-13.

[4] White, T. B., Serratosa, J., Allinson, T., Jones, V. R., Petrovan, S. O., Jobson, B. R., ... & Sutherland, W. J. (2024). Assessing costs and cost-effectiveness across the mitigation hierarchy: An example considering the reduction of bird mortality at power lines. Biological Conservation, 296, 110651.

[5] Ferrer, M., Morandini, V., Baumbusch, R., Muriel, R., De Lucas, M., & Calabuig, C. (2020). Efficacy of different types of “bird flight diverter” in reducing bird mortality due to collision with transmission power lines. Global Ecology and Conservation, 23, e01130.

[6] Moreira, F., Martins, R. C., Aguilar, F. F., Canhoto, A., Martins, J., Moreira, J., & Bernardino, J. (2023). Long-term management practices successfully reduce bird-related electrical faults in a transmission grid increasingly used by white storks for nesting. Journal of Environmental Management, 327, 116897.

[7] Hogan, A., Blomqvist, E., Cochez, M., d’Amato, C., Melo, G. D., Gutierrez, C., ... & Zimmermann, A. (2021). Knowledge graphs. ACM Computing Surveys (Csur), 54(4), 1-37.

[8] Chen, X., Jia, S., & Xiang, Y. (2020). A review: Knowledge reasoning over knowledge graph. Expert systems with applications, 141, 112948.

[9] Chen, Z., Wang, Y., Zhao, B., Cheng, J., Zhao, X., & Duan, Z. (2020). Knowledge graph completion: A review. Ieee Access, 8, 192435-192456.

[10] Ji, S., Pan, S., Cambria, E., Marttinen, P., & Yu, P. S. (2021). A survey on knowledge graphs: Representation, acquisition, and applications. IEEE transactions on neural networks and learning systems, 33(2), 494-514.

[11] Peng, C., Xia, F., Naseriparsa, M., & Osborne, F. (2023). Knowledge graphs: Opportunities and challenges. Artificial intelligence review, 56(11), 13071-13102.

[12] Tiwari, S., Al-Aswadi, F. N., & Gaurav, D. (2021). Recent trends in knowledge graphs: theory and practice. Soft Computing, 25(13), 8337-8355.

[13] Paquet, J. Y., Swinnen, K., Derouaux, A., Devos, K., & Verbelen, D. (2022). Sensitivity mapping informs mitigation of bird mortality by collision with high-voltage power lines. Nature Conservation, 47, 215-233.

[14] Biasotto, L. D., Kindel, A., Pacífico, E. C., Filadelfo, T., Paschotto, F. R., Favoretto, G. R., ... & Ascensão, F. (2025). Mapping priority areas to mitigate the risk of electrocution of range-restricted bird species. Journal of Applied Ecology, 62(10), 2787-2799.

[15] Rebolo-Ifrán, N., Plaza, P., Pérez-García, J. M., Gamarra-Toledo, V., Santander, F., & Lambertucci, S. A. (2023). Power lines and birds: An overlooked threat in South America. Perspectives in Ecology and Conservation, 21(1), 71-84.

[16] Feng, Y., Li, W., Liu, X., & Li, W. (2025, March). Effect of Ultrasonic Bird Repellent on Pigeon Behavior. In 2025 8th International Conference on Advanced Algorithms and Control Engineering (ICAACE) (pp. 1969-1973). IEEE.

[17] Silva, J. P., Marques, A. T., Bernardino, J., Allinson, T., Andryushchenko, Y., Dutta, S., ... & Collar, N. J. (2023). The effects of powerlines on bustards: how best to mitigate, how best to monitor?. Bird Conservation International, 33, e30.

[18] Durgapersad, K., Beutel, A., & Mahatho, N. (2025). Literature Review on Mitigation Measures for Bird Electrocutions Occurring Due to Streamers on Transmission Power Lines. Birds, 6(1), 5.