

# Using fuzzy logic to generate conditional probabilities in Bayesian belief networks: a case study of ecological assessment

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**Abstract** The survival of rare animals is an important concern in an environmental impact assessment. However, it is very difficult to quantitatively predict the possible effect that a development project has on rare animals, and there is a heavy reliance on expert knowledge and judgment. In order to improve the credibility of expert judgment, this study uses Bayesian belief networks (BBN) to

visually represent expert knowledge and to clearly explain the inference process. For the case study, the primary difficulty is in determining a large amount of conditional probabilities in the BBN, because there is a lack of sufficient data concerning rare animals. Therefore, a new method that uses fuzzy logic to systematically generate these probabilities is proposed. The combination of the BBN and the fuzzy logic system is used to assess the possible future population status of the *Pheasant-tailed jacana* and the associated probabilities, which have been affected by the construction of the Taiwan High-Speed Rail. The analysis shows that a restoration program would successfully preserve the species, because in the restoration area, the BBN model predicts that there is a 75.49 % probability that the species will flourish in the future.

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## Introduction

Environmental impact assessment (EIA) is a procedural tool which involves the processes of identification, prediction, evaluation, and mitigation of the biophysical, social, and other relevant effects of development projects, before major decisions and commitments are made (Petts 1999). Development projects for which there is a possibility of adverse impact on the environment must submit an environmental impact assessment report (EIAR), and this EIAR must then be forwarded to competent authorities for review. A development project is refused if its adverse impact is significant. Usually, the survival of rare animals is an important criterion in determining whether the impact of a development project is significant. A study of the 34

EIARs for road construction in Taiwan over the past 5 years (2007–2011) shows that, in practice, the tools that are usually used to estimate the degree of the impact on protected or rare animals mostly rely heavily on expert knowledge and judgment, alone, and make limited use of empirical data. Despite the continued advances in empirical or statistical methods for complex and dynamic ecosystems, most EIARs still use expert opinion, when assessing the impact on rare animals. One possible reason for this is that there is difficulty in obtaining sufficient scientific information that enables the complicated cause-and-effect relationships between a variety of stressors (external intervention and change in the physical, chemical, biological, and natural environment) and a receptor (a specific rare animal) to be identified, so changes made by man that affect rare animals cannot be adequately quantified, but experts can qualitatively forecast the possible consequences for rare animals that result from development projects. Aside from its use in forecasting the impact on rare animals, expert judgment is widely used in biological conservation, partially because of the complexity of the problems encountered, the relative lack of data, and the imminent nature of many conservation decisions (Martin et al. 2012).

Although expert judgment can be used to assess the impact on rare animals, in an EIS, it is usually criticized, because decisions are made in isolation, based on intuition or conjecture, so the reason for the judgment is not often readily explicable. In order to address this concern, methods that can explicitly express expert knowledge and clearly explain the process of inference are required. A total of 36 studies, which are described in the next paragraph, have demonstrated the utility of BBNs (Pearl 1988) in garnering and integrating expert knowledge and empirical data concerning ecological issues. The BBN is a directed acyclic graph with nodes, which denotes a set of random variables as nodes and arrows. These indicate the probabilistic cause-and-effect dependencies. A number of properties make it particularly useful for ecological applications; it allows the use of a combination of qualitative knowledge and quantitative data (Aguilera et al. 2011), so it can easily cope with missing data and it can be constructed using observed data, other models, or expert knowledge. It is a useful tool for risk assessment, because it explicitly incorporates uncertainty in relationships. It is also useful in ecological risk management, because the effects are identified, given the causes, or the causes, given the effects (Hart and Pollino 2008).

The number of studies concerning the application of the BBN for ecological issues has dramatically increased, in recent years. A total of 36 relevant papers have been published and most of these (28 out of 36) were published after 2006. This demonstrates the potential of BBN for use

in ecological issues. The BBN has been used for a variety of predictions, assessments, and characterizations of ecological issues, such as population health, or the future status of fish stocks (Rieman et al. 2001; Borsuk et al. 2003, 2004, 2006; Pollino et al. 2007a; Shenton et al. 2011; Nicholson and Flores 2011; Vilizzi et al. 2012; Chan et al. 2012), amphibians (Wilson et al. 2008), small passerines (Howes et al. 2010), endangered *Eucalyptus camphora* (Pollino et al. 2007b), terrestrial lichens (Nyberg et al. 2006), the prediction of the spatial distribution of species (Walton and Meidinger 2006; Aguilera et al. 2011; Grech and Coles 2010; Dlamini 2011), the viability of populations of at-risk species (Marcot et al. 2001; Steventon et al. 2006), fish production capacity (Hammond and Ellis 2002; Uusitalo et al. 2005), the success of cheetah relocation (Johnson et al. 2010), net ecosystem metabolism in an estuary (Young et al. 2011), large-scale coral bleaching (Wooldridge and Done 2004), reef condition (Shenton et al. 2010), the prediction of the coverage of coral reef macroalgae (Renken and Mumby 2009), bloom initiation for *Lyngbya majuscula* (Hamilton et al. 2007), habitat conditions (Raphael et al. 2001; Sadoddin et al. 2005; McNay et al. 2006; Smith et al. 2007) and in combination with management strategies (Marcot et al. 2006; Gibbs 2007; Bashari et al. 2008; Newton 2010; Helle et al. 2011). Table 1 shows five characteristics (and their options), as detailed in the review paper by Aguilera et al. (2011). These are used to analyze the 36 papers in terms of variables (discrete, continuous, both), model learning (data/simulation, experts/literature, both), and evaluation (train

**Table 1** Distribution of five characteristics over the options for the 36 papers analyzed

Characteristic	Options	Total	%
Variable	Discrete	33	91.6
	Continuous	2	5.6
	Both	1	2.8
Establishment of BBN structure	Experts/literature	26	78.8
	Data/simulation	3	8.38
	Not available	7	19.4
Generation of CP	Experts/literature	20	55.5
	Data/simulation	10	27.8
	Both	6	16.7
Software	Netica	16	44.4
	Hugin	4	11.2
	Others	16	44.4
Evaluation	Sensitivity analysis	15	41.6
	Train and test	4	11.1
	Hybrid	6	16.7
	Cross validation	1	2.8
	Not available	10	27.8



and test, sensitivity analysis, hybrid, cross validation, not available).

Usually, the values for each node in the BBN are categorized into a finite number of levels. The greater the number of levels, the more complex and precise is the model, but the greater is the amount of data required to construct conditional probabilities (CPs). In practice, 2–10 levels are usually used in ecological studies (Uusitalo 2007). In this research, five levels are used, producing 19,625 CPs in the BBN model of the case study. However, it is extremely difficult to obtain sufficient data (whether field data or expert survey) for the rare animal, the *Pheasant-tailed jacana*, to construct these CPs, so subjective judgment is used. This is also known as an expert-driven BBN (Oteniya 2008; Radliński 2013). Similarly, 55.5 % of the related papers (Table 1) use expert opinion or literature to populate the CPs, in the cases where very little empirical data are available, but none detail how the expertise is converted into CPs.

The expert-driven methods used to generate CPs can be approximately classified into three groups: the direct assignment method, the weighted sum algorithm, and fuzzy fault tree (FFT) analysis. The first group of researchers used the direct assignment method because the number of the CPs was small and the experts could easily estimate the CPs. While the subjective estimations for the CPs are usually expressed linguistically, several studies (Li and Kao 2005; Ren et al. 2009; Kao et al. 2011; Li et al. 2012) extend the concept of a conventional BBN to allow fuzzy probabilities (fuzzy BBN). The second group of researchers (Das 2004; Baker and Mendes 2010) devised the weighted sum algorithm, which means that experts estimate less CPs, but they must additionally assess the relative strengths (weights) of the influences of the parent-nodes on a child-node. The third group of researchers (Wang et al. 2011; Wang and Xie 2012) mapped FFT into BBNs. In the FFT method, experts directly assign the probabilities in the rules of Takagi and Sugeno model, which represent the uncertain relationships among different events, so these are the CPs in the BBN. The direct assignment method, the weighted sum algorithm, or FFT analysis are not suitable for this study, because of the large amount of CPs (19,625) in the case study. Therefore, a new expert-driven method to generate a large amount of CPs is proposed, which employs fuzzy logic (Zadeh 1996, 2002) to construct less heuristic rules elicited from experts and to automatically infer more CPs, using these rules.

The use of BBN or fuzzy logic in environmental science and technology is common, as seen in the studies of Liu et al. (2012, 2013), Tuzkaya and Gulsun (2008), Tuzkaya

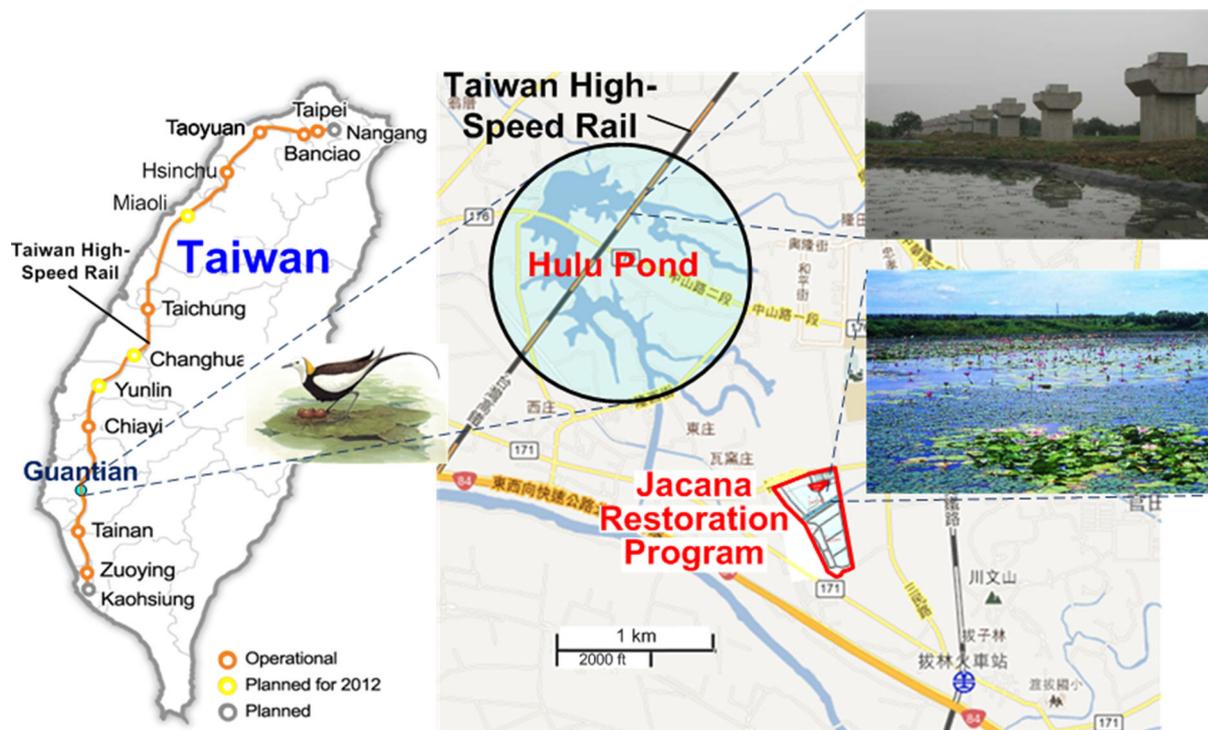
et al. (2009), Karimi et al. (2011), Bangian et al. (2012) and Tuzkaya (2013), but the combination of fuzzy logic and BBN in this field or in ecology is not quite seen in literatures. In this study, fuzzy logic is integrated into the BBN model as an ecological assessment tool for EIA. Finally, the assessment of the future population status of the *Pheasant-tailed jacana* due to the construction of the Taiwan High-Speed Rail (THSR) is used as a case study, in order to demonstrate the use of the method. This research was undertaken by the Department of Safety, Health and Environmental Engineering, Ming Chi University of Technology (Taipei; Taiwan), from August 2011 to July 2012.

## Materials and methods

### Case study

The rugged central mountainous terrain of Taiwan has hindered the population and socio-economical growth, so economic activity has mainly developed along the plains of the West Coast. The increasing demands for north–south intercity transportation led to the birth of the THSR system. In 1987, because of the deteriorating quality and saturation of the transportation system in the Western Corridor, the Executive Yuan commissioned the Taiwanese Transportation Bureau to undertake a feasibility study for a High-Speed Rail System in the Western Corridor. The aim of this study was to improve the transportation service in this area and to coordinate with the metropolitan rapid transport system plan for the construction of a complete transportation network. After almost 13 years of preparation and planning, the construction work for the THSR system began on March 27, 2000. The THSR project, the route of which is mapped in Fig. 1, is not only one of the most challenging infrastructure projects in the world, to date, but also boasts the largest private sector investment in a public construction project. The total investment needed for construction was approximately USD 18 billion. The planned system was 344.68 km in length, including 252 km of overpasses and 48 km of tunnels and revenue service commenced in 2006. The THSR line runs from Taipei to Kaohsiung, passing 14 major cities and counties and 77 townships and regions, including Guantian. Guantian is an agricultural town in Tainan County, well known for its water caltrop farms and produce. Due to the abundance of water caltrop farms and other water-based vegetation farms, Guantian is also an important habitat for many species of water birds especially the rare *Pheasant-tailed jacana*.





**Fig. 1** The major habitat of the *Pheasant-tailed jacanas*, Hulu pond, and its disturbance by the construction of the THSR

The *Pheasant-tailed jacanas* are found in Southern China, the Philippines, and the Middle of the Southern Peninsula, as well as in Taiwan. The rear of the jacana's neck is golden in color and its feathers are dazzling. The males take on the responsibility for the incubation of the eggs and the care of the hatchlings. The jacana is a conspicuous and unmistakable bird that builds its nest on the water caltrops, lotus leaves, and other floating vegetation, in order to prevent attack from land predators. In accordance with the studies by Deng (2002, 2010), Chen (2008), Chiu (2004) and Ueng (2008), several essential survival factors influencing the future population status of the *Pheasant-tailed jacana* are shown in Fig. 2. Brushwood and shrubbery provide a buffer against enemies; swampland is a place for nesting; embankments prevent disturbance to breeding and also provide shelter from cold winds; water caltrop is also an important place for nesting, foraging, and resting; mud is essential for winter foraging; rice is the secondary food source; water quality influences survival; and finally, exterior threats from human disturbance or predators also affect the future population status. These factors determine the suitability of breeding environment, hibernacula surrounding, foraging condition, and habitat (see Fig. 2).

*Pheasant-tailed jacanas* used to be quite a common sight on farmlands in Taiwan. However, the development of freeways through different ponds, farmland, and other water caltrop production regions has caused a decrease in wetland habitats and has resulted in a severe reduction in their numbers. Today, the *Pheasant-tailed jacana* is one of the most endangered bird species in the world. Therefore, the number of the *Pheasant-tailed jacana* is an indicator of the success of any complete fully functioning wetland ecosystem where the *Pheasant-tailed jacana* is to be found. Unfortunately, the THSR was built across the most important habitat for the *Pheasant-tailed jacana*, Hulu pond, and many water caltrop farms and jacana's natural habitat were disturbed, as shown in Fig. 2.

In this study, four scenarios for the future population status of the *Pheasant-tailed jacanas* are discussed in the EIA report. The first scenario is the baseline condition (BC). Hulu pond is the largest, stable habitat for the jacana because it contains a large amount of water chestnut. However, in winter, water chestnut wilt and no floating leaves are available, so the jacana must live in ditches, abandoned fishponds, or riverbanks, leading to their predation by dogs or other animals. Suitable ponds for the jacana usually have deep embankments, but in the Hulu pond many embankments are



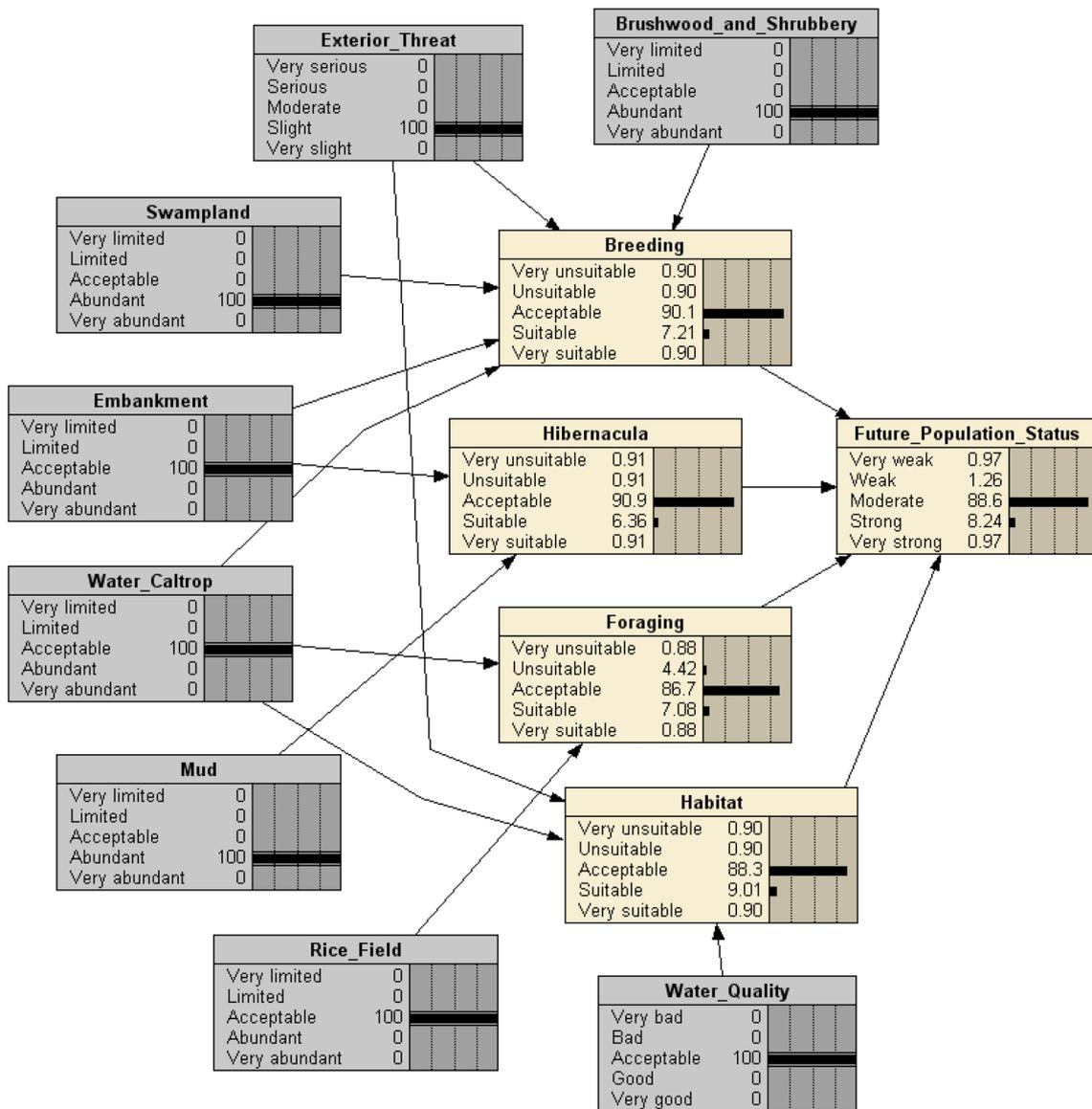


Fig. 2 Essential survival factors influencing the future population status of the Pheasant-tailed jacana (shown by the BBN model)

shallow, which causes a lack of shelter and allows interference from the outside. In addition, illegal industrial wastewater from the nearby Kuantien Industrial Park has been discharged into the pond, leading to eutrophication in the pond, and the excessive use of pesticides in the surrounding agricultural areas has polluted the water. The second scenario is the prediction of the impact without mitigation measures (PIWOM). During the construction of the THSR, personnel, vehicles, and construction equipment cause noise, vibration, and pollution, which seriously affects the breeding, foraging, habitat, and hibernacula of the jacana. The third scenario is the prediction of the impact with mitigation measures (PIWM). The mitigation measures include reducing the scale of construction in the area, using low-noise construction equipment/technology and avoiding building

piers in the pond. Waste soil and wastewater are also prevented from being discharged into the pond, to avoid pollution of the water. The construction period should also take account of the ecology of the jacana, and construction should be avoided from October to April. The fourth scenario is the prediction of the impact with a restoration program (RP). Tainan County and THSR reserved a district approximately 2 km away from Hulu pond, to create a habitat in which the jacanas can live and breed. This land was chosen because it is a potential wetland close to breeding populations (Hulu pond) and is an easily accessible water resource (Chi-Nan irrigation system). The land is divided into two parts of 7 and 8 hectares on each side by Chi-Nan irrigation system. The 7-hectare area to the north includes a large pool, two small ponds, and a nursery pond. There are another four large

ponds in the 8-hectare area to the south. Water chestnuts will be planted in the early phase, and more aquatic plants will be added in the future. Winter is usually dry and the water supply is scarce in southern Taiwan, but because the ponds to the south are deeper they are able to retain enough water to ensure the survival of animals. In winter, when water chestnuts die, other than putting in man-made islands, fragrant lilies and aquatic plants that grow in the winter will be

planted in the ponds, to make them more habitable for the jacanas in winter. The detailed information for the four scenarios is shown in Table 2.

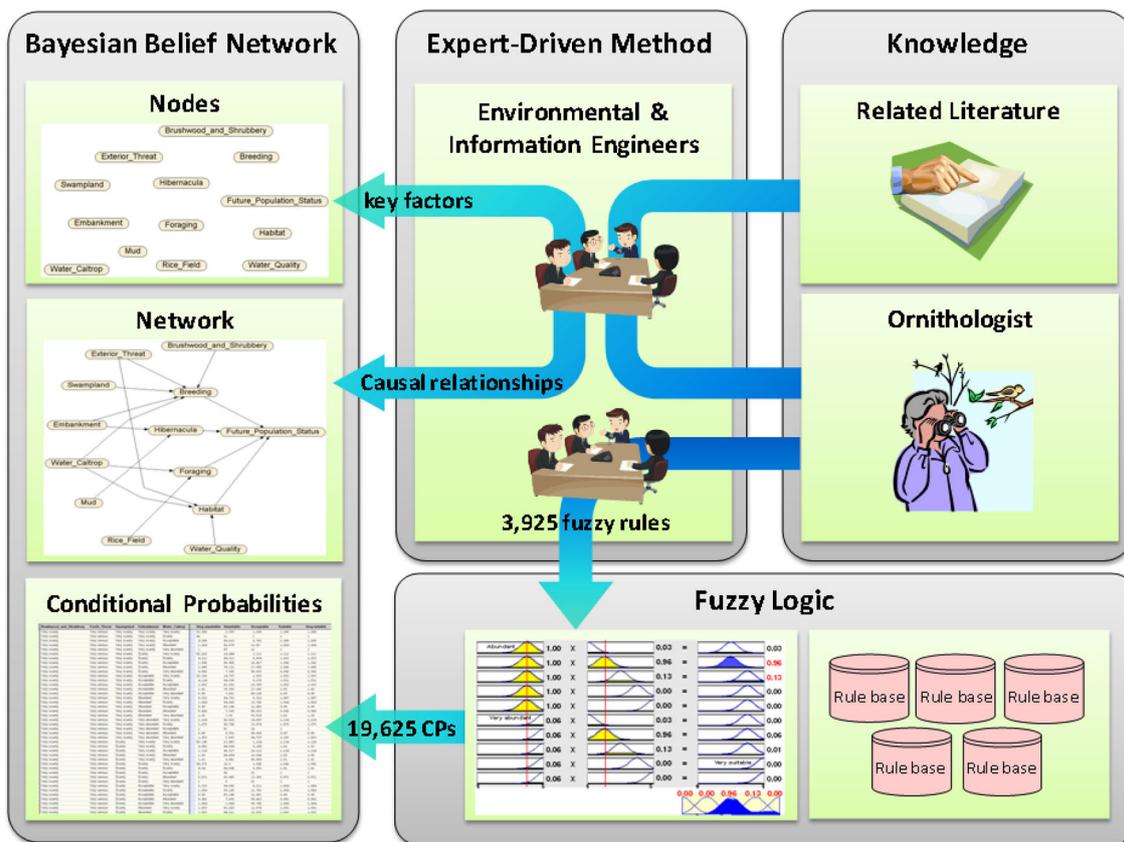
**Table 2** The detailed information for the four scenarios

Scenario	BC	PIWOM	PIWM	RP
Brushwood and shrubbery	Abundant	Acceptable	Acceptable	Very abundant
Exterior threat	Slight	Serious	Moderate	Slight
Swampland	Abundant	Limited	Acceptable	Abundant
Embankment	Acceptable	Limited	Limited	Abundant
Water caltrop	Acceptable	Limited	Acceptable	Very abundant
Mud	Abundant	Limited	Acceptable	Very abundant
Rice field	Acceptable	Acceptable	Acceptable	Acceptable
Water quality	Acceptable	Bad	Acceptable	Very abundant

**Bayesian belief network**

A BBN is a directed acyclic graph wherein the nodes represent random variables ( $X_i$ ) that have several possible states and the arrows connect pairs of nodes and show their probabilistic cause-and-effect relationships. Each node with parents is associated with a conditional probability table that contains many CPs and quantifies the uncertain effects that the parents have on the node; those nodes without a parent have a probability distribution over all possible states. These probabilities are evaluated using historical data, expert judgment, or a combination of both, as shown in Table 1. A BBN has an associated computational structure, so it can calculate the bi-directional propagations of beliefs between nodes and ultimately determine a probability distribution over all possible states for each node, for a given set of evidence. This feature can be used to test scenarios, under either data-driven or goal-driven circumstances.

There are three important elements in the development of a BBN (Liu et al. 2012): nodes (key factors), networks



**Fig. 3** The development procedure for an expert-driven BBN using fuzzy logic

**Table 3** The 125 conditional probabilities for the suitability of the foraging environment

No	Water caltrop (1–5)	Rice field (1–5)	Foraging (%)				
			Very unsuitable	Unsuitable	Acceptable	Suitable	Very suitable
1	Very limited	Very limited	86.7	10.5	1.0	1.0	1.0
2	Very limited	Limited	83.3	13.9	0.9	0.9	0.9
3	Very limited	Acceptable	5.1	90.9	2.0	1.0	1.0
4	Very limited	Abundant	0.9	86.5	10.8	0.9	0.9
5	Very limited	Very abundant	0.9	84.5	12.7	0.9	0.9
6	Limited	Very limited	4.1	91.8	2.1	1.0	1.0
7	Limited	Limited	3.7	85.2	9.3	0.9	0.9
8	Limited	Acceptable	0.9	88.1	9.2	0.9	0.9
9	Limited	Abundant	0.9	6.5	90.7	0.9	0.9
10	Limited	Very abundant	0.9	3.5	84.3	10.4	0.9
11	Acceptable	Very limited	0.9	86.5	10.8	0.9	0.9
12	Acceptable	Limited	1.0	5.7	91.4	1.0	1.0
13	Acceptable	Acceptable	0.9	4.4	86.7	7.1	0.9
14	Acceptable	Abundant	0.9	0.9	90.1	7.2	0.9
15	Acceptable	Very abundant	0.9	0.9	9.2	88.1	0.9
16	Abundant	Very limited	0.9	6.6	86.8	4.7	0.9
17	Abundant (3.988)	Limited (2.126)	0.9	0.9	85.7	11.6	0.9
18	Abundant	Acceptable	0.9	0.9	7.2	90.1	0.9
19	Abundant	Abundant	0.9	0.9	6.9	86.2	5.2
20	Abundant	Very abundant	0.9	0.9	0.9	91.7	5.5
21	Very abundant	Very limited	1.0	1.0	7.8	89.2	1.0
22	Very abundant	Limited	0.9	0.9	6.4	90.9	0.9
23	Very abundant	Acceptable	0.9	0.9	0.9	89.1	8.2
24	Very abundant	Abundant	0.9	0.9	0.9	8.1	89.2
25	Very abundant	Very abundant	0.9	0.9	0.9	6.4	90.9

(causal relationships), and CPs (uncertainty causal relationships). For the assessment of rare animals, there is no relevant information, so these three elements are established by means of an expert panel. The expert panel consists of the authors: an ornithologist and several specialists in environmental management or information systems, who formulate the BBN model according to the guidelines proposed by Marcot et al. (2006), as shown in Fig. 3. Firstly, the experts identify the key factors affecting the *Pheasant-tailed jacana*, as detailed by related literature, to create influence diagrams and develop an initial, tentative BBN model. The tentative BBN model is then revised following an interview with the ornithologist. The fuzzy logic system is then designed by the expert panel and the associated 3,925 fuzzy rules are extracted from the information provided by the ornithologist. The 19,625 CPs are determined using the fuzzy logic system. An iterative process is then used to calibrate the fuzzy rules, before a final workable set of CPs is produced, which creates the final BBN model.

The use of fuzzy logic to generate CPs

It is very difficult for experts to evaluate the 19,625 CPs; therefore, fuzzy logic is used to help the experts. For example, the suitability of the foraging environment is determined by the conditions of the water caltrop and rice fields; the 125 CPs are shown in Table 3. The five CPs in row no. 17 of Table 3,  $P = (\text{Foraging} = \text{water caltrop} = \text{abundant and rice field} = \text{limited})$ , demonstrate the derivation of the fuzzy logic.

Fuzzy logic (Zadeh 1996, 2002) is a tool with the ability to compute with words for the analysis of complex systems and decisions, in order to model qualitative human thought processes. Fuzzy logic represents qualitative perception-based reasoning by “IF–THEN” fuzzy rules, which makes it easier for experts to express their judgment of CPs. In the suitability of foraging example, the evaluation rules for generating the associated CPs are easily seen in Table 4, where “water caltrop,” “rice field,” and “the suitability of



**Table 4** Fuzzy rules for generating the CPs of foraging environment

Rule No	IF part		THEN part
	Water caltrop	Rice Field	Foraging
1	Very limited	Very limited	Very unsuitable
2	Very limited	Limited	Very unsuitable
3	Very limited	Acceptable	Unsuitable
4	Very limited	Abundant	Unsuitable
5	Very limited	Very abundant	Unsuitable
6	Limited	Very limited	Unsuitable
7	Limited	Limited	Unsuitable
8	Limited	Acceptable	Unsuitable
9	Limited	Abundant	Acceptable
10	Limited	Very abundant	Acceptable
11	Acceptable	Very limited	Unsuitable
12	Acceptable	Limited	Acceptable
13	Acceptable	Acceptable	Acceptable
14	Acceptable	Abundant	Acceptable
15	Acceptable	Very abundant	Suitable
16	Abundant	Very limited	Acceptable
17	Abundant	Limited	Acceptable
18	Abundant	Acceptable	Suitable
19	Abundant	Abundant	Suitable
20	Abundant	Very abundant	Suitable
21	Very abundant	Very limited	Suitable
22	Very abundant	Limited	Suitable
23	Very abundant	Acceptable	Suitable
24	Very abundant	Abundant	Very suitable
25	Very abundant	Very abundant	Very suitable

foraging” are linguistic variables (Zadeh 1975) and “very limited,” “limited,” “acceptable,” “abundant,” “very abundant,” “very unsuitable,” “unsuitable,” “acceptable,” “suitable,” and “very suitable” are the possible fuzzy values, which are defined by Gaussian distribution, as shown in Fig. 4. Instead of widely used triangular membership functions, the Gaussian distribution is used herein because a study (Mandal et al. 2012) has made a comparison among the predicted data using different membership functions and it indicated that the Gaussian distribution has less error in prediction of data than the triangular one.

In order to account for any bias due to subjective judgment, the values for “water caltrop = abundant” and “rice field = limited” are randomly selected around the peak of the Gaussian distributions; they are 3.988 and 2.126, respectively. The two values are fed into this inference mechanism and fuzzy logic proceeds. Fuzzy logic is easily explained using a graphical representation, as shown in Fig. 4. This figure shows the three major steps

involved in inferring a conclusion, using fuzzy reasoning (Liu and Lai 2009): computing compatibility, truncating conclusions, and aggregating truncated conclusions. The first step defines compatibility as the similarity of an antecedent, which refers to a fact having the same linguistic variable, or the suitability of a specific rule with regard to several facts, as its respective antecedents. For Rule 13, the compatibility of “water caltrop = abundant” with “water caltrop = acceptable” is 0.07, and for “rice field = limited,” its compatibility with “rice field = acceptable” is 0.13, so the overall compatibility of Rule 13 with the four facts is  $0.07 \times 0.13$ , which is 0.01. It should be noted that “algebraic product” is chosen as the t-norm operator, rather than using another more widely used t-norm operator, “min,” because the t-norm operator, “product,” makes the conclusion sensitive to every input, whereas only one input controls the conclusion in the case of the t-norm operator, “min.” The compatibility of other rules is calculated in the same way. The second step computes the degree to which the antecedents are satisfied by each rule. As shown in Fig. 4, a new conclusion is then inferred, by truncating the Gaussian conclusion of each rule with its corresponding compatibility. The last step aggregates several inferred conclusions with the same linguistic variable. Aggregation is the process by which the fuzzy sets representing the truncated conclusions of triggered rules are combined into a single fuzzy set. In Fig. 4, the final conclusion is aggregated by taking the union of all truncated conclusions. Ultimately, the conditional possibilities for “the suitability of foraging = very unsuitable,” “foraging = unsuitable,” “foraging = acceptable,” “foraging = suitable,” and “foraging = very suitable” are 0.00, 0.00, 0.96, 0.13, 0.00, respectively. However, the lowest possibility, 0.01, is tolerated in the situation where the possibility is zero because every state of the suitability of foraging is possible and its possibility should be greater than zero. Therefore, these conditional possibilities are further edited, as follows, and their summation is 1.12.

$$\text{Poss}(\text{Foraging} = \text{very unsuitable} \mid \text{water caltrop} = \text{abundant and rice field} = \text{limited}) = 0.01$$

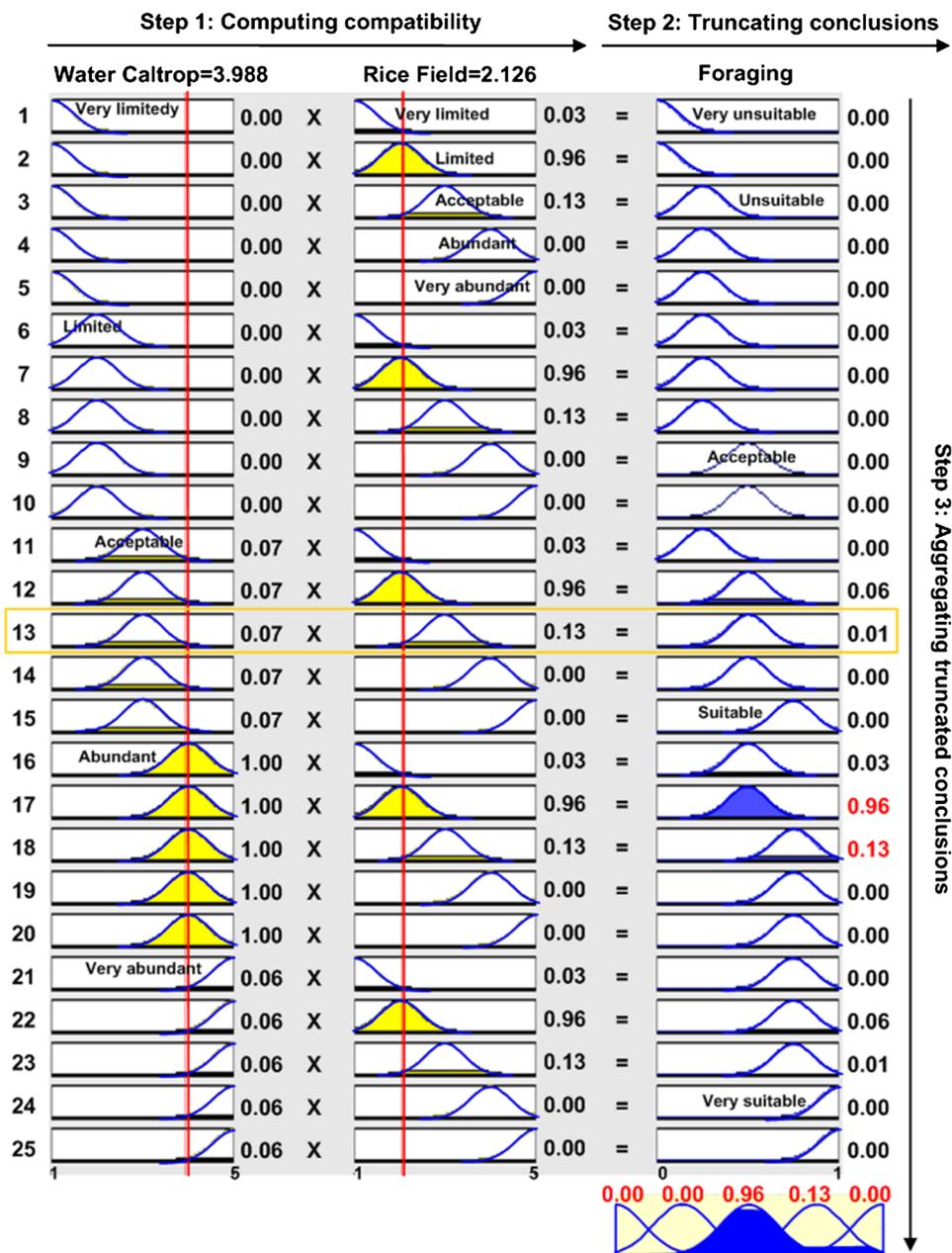
$$\text{Poss}(\text{Foraging} = \text{unsuitable} \mid \text{water caltrop} = \text{abundant and rice field} = \text{limited}) = 0.01$$

$$\text{Poss}(\text{Foraging} = \text{acceptable} \mid \text{water caltrop} = \text{abundant and rice field} = \text{limited}) = 0.96$$

$$\text{Poss}(\text{Foraging} = \text{suitable} \mid \text{water caltrop} = \text{abundant and rice field} = \text{limited}) = 0.13$$



**Fig. 4** Graphical representation of fuzzy logic



Poss(Foraging = very suitable | water caltrop = abundant and rice field = limited) =0.01

The upper bound of a probability measure is the possibility measure (Dubois and Prade 2010), i.e.,  $P(\cdot) \leq \text{Poss}(\cdot)$ . However, the CPs of the suitability of foraging over the five possible states are assumed to be proportional to the CPs. Therefore, the five CPs in row no. 17 of Table 3 are derived as follows:

$P(\text{Foraging} = \text{very unsuitable} \mid \text{water caltrop} = \text{abundant and rice field} = \text{limited}) = 0.01/1.12$

$= 0.009$   
 $P(\text{Foraging} = \text{unsuitable} \mid \text{water caltrop} = \text{abundant and rice field} = \text{limited}) = 0.01/1.12$   
 $= 0.009$   
 $P(\text{Foraging} = \text{acceptable} \mid \text{water caltrop} = \text{abundant and rice field} = \text{limited}) = 0.96/1.12$   
 $= 0.857$   
 $P(\text{Foraging} = \text{suitable} \mid \text{water caltrop} = \text{abundant and rice field} = \text{limited}) = 0.13/1.12$   
 $= 0.116$

P(Foraging = very suitable | water caltrop = abundant and rice field = limited)  
 =0.010/1.12  
 =0.009

## Results and discussion

### Model development and evaluation

A widely used software package, Netica (Norsys Software Corp. Canada), was employed to implement the BBN model. Its graphical user interfaces makes it easy for users to build the network structure manually. It offers a mechanism for learning CPs from cases, but this was not used because of the insufficient number of cases. Instead, the fuzzy logic is used to generate the CPs and is implemented with the MATLAB Fuzzy Logic Toolbox.

Sometimes it is useful to know the degree to which a belief in a particular node is influenced by findings at other nodes. Netica computes a node's "sensitivity to findings," using the mutual information. In probability theory and information theory, the mutual information of two random variables is a quantity that measures the mutual dependence of the two random variables. The mutual information determines which variables and states of variables are more influential, with respect to the target variable. It shows when small changes in the probability of a state cause great changes in the probability distribution of the target variable (Aguilera et al. 2011). The information also helps to identify errors in either the network structure or the CPs and provides guidance for the collection of further data or for eliciting direct expert evaluation (Pollino et al. 2007a). For the case study, the result for the sensitivity to findings is shown in Table 5. For the target node (future population status), the suitability of breeding, the suitability of foraging, water caltrop, and the suitability of habitat are the most crucial survival factors. It should also be noted that water caltrop is the most crucial survival factor for the suitability of breeding, foraging, and habitat, simultaneously, because it provides a space for nesting, foraging, and resting.

### Scenario testing

Four scenarios are considered in the EIA report: the BC, the PIWOM, the PIWM, and the prediction of the impact with a RP. For every scenario, the possible states for each survival factor are shown in Table 2, which are evaluated by authors primarily based on the EIA report and other supplemental materials such as reports (Chiu 2004; Ueng 2008), theses (Chen 2008;

**Table 5** Sensitivity to a target node due to a finding in its relevant survival factors

Target node	Important relevant survival factor	Mutual information
Future population status	Breeding	0.43275
	Foraging	0.37896
	Water caltrop	0.37488
	Habitat	0.35407
	Hibernacula	0.13050
	Embankment	0.08780
	Exterior threat	0.02639
	Mud	0.01906
	Rice field	0.01315
	Water quality	0.00621
Breeding	Swampland	0.00394
	Brushwood and shrubbery	0.00314
	Water caltrop	0.31002
	Embankment	0.08980
Hibernacula	Swampland	0.06019
	Brushwood and shrubbery	0.04809
	Exterior threat	0.03705
Foraging	Embankment	0.62838
	Mud	0.28274
Habitat	Water caltrop	0.78097
	Rice field	0.20053
	Water caltrop	0.43615
	Exterior threat	0.17337
	Water quality	0.08253

Deng 2010), and related discussion on the Internet. The detailed information for the four scenarios (Table 2) is the input of the BBN model, and the probability distribution over all possible states for each survival factor is then obtained, as shown in Table 6. For the BC, the most probable suitability of "breeding" is "acceptable," with the highest probability being 90.09 %; the most probable suitability of "foraging" is "acceptable," with the highest probability being 86.73 %; the most probable suitability of "habitat" is "acceptable," with the highest probability being 88.29 %, and the most probable suitability of "hibernacula" is "acceptable," with the highest probability being 90.91 %. Ultimately, the most probable status of the future population of the *Pheasant-tailed jacanas* is "moderate," with the highest probability being 88.56 %, as demonstrated in Fig. 3 and shown in the BC column of Table 6. Because of the construction work for the Taiwan High-Speed Railway, the most probable suitability of "breeding," "foraging," "habitat," and "hibernacula" is shifted one level to "unsuitable," "unsuitable," "unsuitable," and "unsuitable,"



**Table 6** The derived probability distributions for the survival factors for the four scenarios

Survival factor	State	BC (%)	PIWOM (%)	PIWM (%)	RP (%)
Breeding	Very unsuitable	0.90	0.93	0.94	0.89
	Unsuitable	0.90	87.85	86.79	0.89
	Acceptable	90.09	9.35	10.38	5.36
	Suitable	7.21	0.93	0.94	85.71
	Very suitable	0.90	0.93	0.94	7.14
Foraging	Very unsuitable	0.88	0.92	0.92	0.90
	Unsuitable	4.42	88.07	88.07	0.90
	Acceptable	86.73	9.17	9.17	0.90
	Suitable	7.08	0.92	0.92	89.09
	Very suitable	0.88	0.92	0.92	8.18
Habitat	Very unsuitable	0.90	1.06	0.95	0.89
	Unsuitable	0.90	94.68	4.76	0.89
	Acceptable	88.29	2.13	92.38	0.89
	Suitable	9.01	1.06	0.95	8.93
	Very suitable	0.90	1.06	0.95	88.39
Hibernacula	Very unsuitable	0.90	2.63	2.63	0.90
	Unsuitable	0.90	87.72	87.72	0.90
	Acceptable	90.91	7.89	7.89	0.90
	Suitable	6.36	0.88	0.88	90.09
	Very suitable	0.90	0.88	0.88	7.21
Future population status	Very weak	0.97	1.04	0.96	0.91
	Weak	1.26	84.01	62.53	0.91
	Moderate	88.56	12.78	34.39	2.23
	Strong	8.24	1.12	1.15	75.49
	Very strong	0.97	1.04	0.96	20.45

respectively, and the most probable status of the future population of the *Pheasant-tailed jacanas* is further rated as “weak,” with the highest probability being 84.01 %, as shown in the PIWON column of Table 6.

If the mitigation measures, as described in the EIA report (section “Materials and methods”), are taken, the analysis shows that only the suitability of habitat is improved from “unsuitable” to “acceptable,” because the mitigation measures primarily reduce the disturbance due to construction (exterior threat) and water pollution. The future population of the *Pheasant-tailed jacanas* is then considered to be a combination of “weak,” with a probability of 62.53 %, and “moderate,” with a probability of

34.39 %, as shown in the PIWN column of Table 6. This result implies that the PIWN is not satisfactory. A useful feature of the BBN is that it can help to manage environmental or ecological risk by testing causes, given the hypothetical effects (Hart and Pollino 2008). Assuming that the EIA committee ask the developer to maintain the suitability of “breeding,” “foraging,” “hibernacula,” and “habitat” as “acceptable,” during the construction work, the BBN model suggests that the condition of exterior threat should be improved to the level of “very slight,” with a highest probability of 79.84 %. This “very slight” exterior threat is very difficult or very costly to achieve, during the construction work, because it is better than the “slight” exterior threat for the BC. Another solution is the RP, as described in section “Materials and methods”. The RP largely improves the environmental conditions for the *Pheasant-tailed jacanas*. For the RP, the most probable suitability of “breeding” is “suitable,” with the highest probability being 85.71 %; the most probable suitability of “foraging” is “suitable,” with the highest probability being 89.09 %; the most probable suitability of “habitat” is “very suitable,” with the highest probability being 88.39 %, and the most probable suitability of “hibernacula” is “suitable,” with the highest probability being 90.09 %. Ultimately, the most probable status of the future population of the *Pheasant-tailed jacanas* is “strong,” with the highest probability being 75.49, as shown in the RP column of Table 6.

**Conclusion**

This study proposes a BBN model for ecological assessment in EIA, whose features include the representation of the demonstration of the probabilistic relationships between survival factors and adverse ecological effects, using the graphical structures of the BBN, the construction of stress–response relationships, using the CPs of the BBN, and the capability to predict the population status of a rare animal using the inference mechanism of the BBN. The 19,625 CPs in the BBN model are very difficult to generate, because of the lack of sufficient data concerning rare animals. Therefore, this paper uses fuzzy logic to allow experts to generate these CPs.

In the case study, the status of the future population of the *Pheasant-tailed jacana* is affected by the construction work for the Taiwan High-Speed Railway. In terms of the BC, the most probable status of the future population is “moderate,” with the highest probability being 88.56 %, but this is reduced to “weak,” with the highest probability

being 84.01 %, in the construction phase. It is slightly improved (a combination of “weak,” with a probability of 62.53 %, and “moderate,” with a probability of 34.39 %), if the mitigation measures are taken, but the result is not satisfactory. Ultimately, the RP significantly improves the environmental conditions for the *Pheasant-tailed jacana*, and the most probable status of the future population of the *Pheasant-tailed jacana* is “strong,” with the highest probability being 75.49 %.

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