Model for Efficient Risk Allocation in Privately Financed Public Infrastructure Projects Using Neuro-Fuzzy Techniques

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Abstract: Risk allocation plays a critical role in privately financed public infrastructure projects. Project performance is contingent on whether the adopted risk-allocation strategy can lead to efficient risk management. Founded primarily on the transaction cost economics, a theoretical framework was recently developed to model the risk allocation decision-making process in privately financed public infrastructure projects. In this paper, a neuro-fuzzy model adapted from an adaptive neuro-fuzzy inference system was further designed based on the framework by combining fuzzy logic and artificial neural network techniques. Real project data were used to train and validate the neuro-fuzzy models. To evaluate the neuro-fuzzy models, multiple linear regression models and fuzzy inference systems established in previous studies were used for a systematic comparison. The neuro-fuzzy models can serve the purpose of forecasting efficient risk-allocation strategies for privately financed public infrastructure projects at a highly accurate level that multiple linear regression models and fuzzy inference systems could not achieve. This paper presents a significant contribution to the body of knowledge because the established neuro-fuzzy model for efficient risk allocation represents an innovative and successful application of neuro-fuzzy techniques. It is thus possible to accurately predict efficient risk-allocation strategies in an ever-changing business environment, which had not been achieved in previous studies. **DOI: 10.1061/(ASCE)CO.1943-7862.0000365.** © *2011 American Society of Civil Engineers.*

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Introduction

There has been an ongoing massive demand for infrastructure investment in many countries as a result of rapid social and economic growth (World Bank 2008). However, inefficacies and insufficient governmental funds for infrastructure development are common in the conventional provision of infrastructure. Public-private partnerships (PPPs) have been seen as a mechanism to tackle these problems. Accordingly, a range of PPP arrangements are rapidly becoming the preferred way to provide public services worldwide (Jin and Doloi 2008). Risk transfer is one of the greatest drivers for value-for-money, which is the core principle for PPPs (Victorian Department of Treasury and Finance 2000). That is, appropriate risks can be transferred to the private sector, which is supposed to be capable of managing those risks better (Hayford 2006). Accordingly, cheaper and higher-quality infrastructure services may be provided than in the conventional way.

However, construction projects worldwide manifest more risks than do other industries (Han and Diekmann 2004). In PPP projects, all the parties involved are increasingly exposed to various risks because of the complexity of arrangements and incomplete contracting nature of the PPP mechanism (Jin and Doloi 2008). There is still an incorrect perception that privatization involves transfer of all risks to the private sector (Faulkner 2004). Therefore, sometimes, especially when the government maintains maximum competitive tension, risks will inevitably be allocated to the party least able to refuse them (Thomas et al. 2003). Nonetheless, because the transfer of risks to the private sector comes at a price (Hayford 2006) and improper allocation of risks among stakeholders may lead to higher-than-necessary prices (Thomas et al. 2003), governments should understand that it is suboptimal for them to either retain or transfer inappropriate risks (Arndt 1999).

There have been continuing efforts in investigating which categories of risk governments should generally accept or transfer to achieve an optimal risk allocation. Jin (2010a) recently established a theoretical framework anchored in the transaction cost economics (TCE) and the resource-based view (RBV) of organizational capabilities to interpret in a logical and holistic way the mechanism underlying the decision-making process of how to efficiently allocate a given risk. Optimum statistical models were obtained and important linearly bound determinants identified by using the multiple linear regression (MLR) technique. However, the basically probability-oriented MLR technique was found to be unable to identify all the factors necessary to reflect realistic situations for more accurate prediction purposes, although it is able to identify major constructs of a theoretical framework (Jin 2010a). Therefore, non-probability-oriented techniques have been considered to tackle such issues. Accordingly, fuzzy inference systems (FISs) were developed to model the theoretical framework. However, FIS itself lacks learning ability, which makes the system less suitable for prediction (Jin and Doloi 2009). Consequently, a more suitable

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approach is using an adaptive neuro-fuzzy inference system (ANFIS), which combines the strengths of fuzzy logic (FL) and artificial neural networks (ANNs) and thus possesses the capability to handle the unspecificity, uncertainty, nonlinearity, and complexity that are involved in most risk allocation decision-making (RADM) processes (Jang 1993; Jang and Sun 1995).

However, very few works have been done to apply neuro-fuzzy techniques to modeling RADM processes. Therefore, the major and specific contribution of this paper is the innovative and successful application of neuro-fuzzy techniques to establishing a neuro-fuzzy model for efficient risk allocation in PPP infrastructure projects so that an accurate prediction of efficient risk-allocation strategies becomes possible in an ever-changing business environment. To evaluate the performance of the neuro-fuzzy model, the results when using the neuro-fuzzy model are compared with those using MLR technique (see Jin 2010a) and FIS models (see Jin and Doloi 2009). Additionally, in this paper, a fuzzy operation method is also adopted to obtain an indicator to index environmental uncertainty, by which the curse of dimensionality, often caused by too many variables, is tackled. Equally importantly, the TCE and RBV theories have been further proved to be suitable for explaining RADM processes. In the following sections, first, the theoretical framework is briefly revisited. A neuro-fuzzy RADM model is then built to forecast efficient risk-allocation strategies in PPP infrastructure projects. This is followed by a detailed report on the research method and the development, training, and evaluation of the model. Finally, a conclusion is presented.

Framework of Making Efficient Risk Allocation Decisions

A theoretical framework has been proposed by Jin (2010a) for interpreting risk allocation mechanisms in PPP projects based on TCE and the RBV of organizational capability. Transaction costs are the costs of running the economic system (Arrow 1969). The TCE poses the problem of economic organization as a problem of contracting and assumes that (1) human agents are subject to bounded rationality, in which behavior is "intendedly rational but only limitedly so" (Simon 1961, p. xxiv); and (2) human agents are given to opportunism, which is a condition of "self-interest seeking with guile" (Williamson 1985). TCE further maintains that there are rational economic reasons for organizing some transactions one way and other transactions another. The principal dimensions by which transactions differ are asset specificity, uncertainty, and frequency (Williamson 1996). By assigning transactions to governance structures in a discriminating way, transaction costs are economized (Williamson 1985).

Choosing a risk-allocation strategy was actually viewed as a process of deciding the proportion of risk management responsibility between internal and external organizations based on a series of characteristics of the risk management service transaction in question (Jin 2010a). RADM in PPP projects is suitable to be viewed from a TCE perspective because any issue that can be formulated as a contracting problem can be investigated to advantage in transaction cost–economizing terms (Williamson 1985). Additionally, many features of PPPs, including incomplete contracting, long-term partnerships, heavy investment in assets, and complex uncertainty, also ensure such suitability (Jin 2010a). Jin (2010a) also emphasized that both production and governance costs must be taken into account in any analysis adopting the TCE approach. This is because the objective of TCE is not to minimize production and governance costs separately, but to economize on the total cost of a transaction (Williamson 1985, 1996). Therefore,

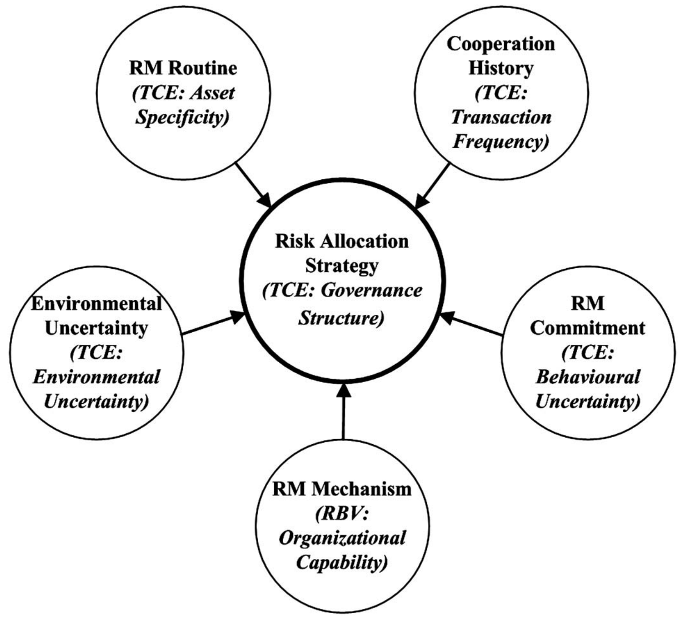

Fig. 1. Theoretical framework for making risk-allocation decisions in PPP infrastructure projects (Jin 2010a, ASCE)

organizational capability, on which production costs are greatly contingent (Jacobides and Hitt 2005), should be taken into consideration when seeking efficient governance structure (Jin 2010a). Among various theories dedicated to organizational capabilities, the RBV of organizational capability has been recognized as the one that is most capable of explaining competitive heterogeneity based on the premise that close competitors differ in their capabilities and resources in important and durable ways (Helfat and Peteraf 2003).

Following the TCE and the RBV theories, the characteristics of a risk management service transaction can be categorized as the following: (1) private partner's RM (risk management) routines, which embody competence in carrying out RM activities and indicate that alternative uses could have been achieved without sacrificing productive value (reversely approximating supplier's asset specificity of TCE); (2) partners' cooperation history (approximating transaction frequency of TCE); (3) partners' RM commitment (reversely matching behavioral uncertainty of TCE); (4) RM environmental uncertainty (matching environmental uncertainty of TCE); and (5) partners' RM mechanism (approximating the organizational capability of RBV) [see Jin (2010a) for a detailed discussion]. Accordingly, a theoretical framework was established, as shown in Fig. 1. For different combinations of the status of these characteristics, there exists different risk-allocation strategies for achieving efficiency (Jin 2010a).

Neuro-Fuzzy Modeling Techniques

The theoretical framework was tested by using the MLR technique (Jin 2010a). Generally, the decision on how much risk to transfer to the private partner was actually made complying with the TCE and RBV theories (Jin 2010a). Nonetheless, the framework cannot be used to forecast efficient risk-allocation strategies because of the inherent limitations in MLR analysis. These limitations include only considering linear relationships, probability orientation, and lack of ability to identify all the factors necessary to reflect realistic situations (Tsoukalas and Uhrig 1997). Therefore, non-probability-based analysis techniques are required, and nonlinear

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relationships must be considered for accurately modeling RADM process (Jin 2010a). Accordingly, fuzzy inference systems were developed, illustrated, and evaluated to model the theoretical framework (Jin and Doloi 2009). Nonetheless, a more suitable approach is the adaptive neuro-fuzzy inference system, which combines the strengths of fuzzy logic and artificial neural networks and thus possesses the capability to handle the unspecificity, uncertainty, nonlinearity, and complexity (Jang 1993; Jang and Sun 1995) that are involved in most RADM processes (Jin and Doloi 2008). Additionally, ANN's strong learning ability helps to make the system suitable for prediction (Jin 2010b). A detailed discussion on FL and ANN is beyond the scope of this paper. Only the FIS and the ANFIS are briefly introduced as follows.

Based on FL, the fuzzy reasoning technique is close to the process of inference from commonsense knowledge (Tanaka 1997; Zadeh 1986). Fuzzy linguistic descriptions, often called fuzzy inference systems, are formal representations of the systems made through fuzzy if-then rules. They offer an alternative and often complementary language to conventional approaches to modeling systems. FIS has rigorous mathematical foundations involving fuzzy sets and fuzzy relations, although they are formulated in human language (Zadeh 1988). They encode knowledge about a system in the statement of fuzzy if-then rules (Kartakapoulos 1996). These rules represent the knowledge and heuristic rules in a given area. There have been a number of efforts in using fuzzy logic in the domain of risk management in construction projects, such as Kangari (1988), Kangari and Riggs (1989), Chun and Ahn (1992), Tah et al. (1993), Peak et al. (1993), Wirba et al. (1996), and Tah and Carr (2000), among many others. Nonetheless, very few works have focused on the application of fuzzy logic to risk allocation. Lam et al. (2007) designed a decision model for risk allocation in which linguistic principles and experiential expert knowledge were transformed into a quantitative-based analysis by using fuzzy logic. However, their risk allocation criteria were not based on associated theories but solely established by expert knowledge.

On the other hand, the use of ANN techniques allows empirical information to be embedded into a fuzzy system. This greatly expands the range of applications in which fuzzy systems can be used and enhances the utility of fuzzy systems. An ANN is a massive parallel distributed processor made up of simple processing units. It has a natural propensity for storing experiential knowledge and making it available for use (Lin and Lee 1996). Owing to their excellent learning and generalizing capabilities, ANN techniques have been applied in a variety of construction domains, including estimating project markup (Li 1996; Li and Love 1999; Moselhi et al. 1991), forecasting construction productivity (Chao and Skibniewski 1994), predicting potential to adopt new construction technology (Chao and Skibniewski 1995), modeling construction budget performance (Chua et al. 1997), predicting earth-moving operations (Shi 1999), forecasting residential construction demand (Goh 2000), predicting project cost (Emsley et al. 2002), simulating activity duration (Lu 2002), predicting cost deviation in reconstruction projects (Attalla and Hegazy 2003), forecasting client satisfaction levels (Soetanto and Proverbs 2004), identifying building natural periods (Kuźniar and Waszczyszyn 2006), and estimating equipment productivity (Ok and Sinha 2006), among many others.

There are many merging formats of ANN and FL, such as neuro-fuzzy inference systems (in which an ANN is used as a tool in fuzzy models), fuzzy artificial neural networks (in which conventional ANN models are fuzzified), and fuzzy-neural hybrid systems (in which fuzzy technologies and ANNs are incorporated into hybrid systems) (Lin and Lee 1996). In this paper, the adaptive neuro-fuzzy inference system was adopted for developing a neuro-fuzzy model. The ANFIS was proposed by Jang (Jang 1993; Jang and Sun 1995) to identify a set of parameters through a hybrid learning rule combining the gradient descent–based back-propagation (BP) optimization method and the least-squares estimator (LSE) method. Fundamentally, ANFIS is a graphical network representation of zero-order or first-order Sugeno-type FIS endowed with neural learning capabilities (Jang and Sun 1995). The network is comprised of nodes and specific functions collected in layers (Tsoukalas and Uhrig 1997). Sugeno FIS, also known as TSK (Takagi-Sugeno-Kang) FIS, was proposed in an effort to develop a systematic approach to generating fuzzy rules from a given input/output data set (Sugeno 1985; Sugeno and Kang 1988; Takagi and Sugeno 1983). The output membership functions (MFs) of Sugeno FIS are either linear or constant. Because of the linear dependence of each rule on the input variables, a Sugeno-type FIS is compact and computationally efficient. Therefore, the Sugeno-type FIS is suitable for the use of adaptive techniques, which can be used to customize the MFs so that the FIS can better model the data (MathWorks 2007). Nonetheless, future research may test neuro-fuzzy models based on Mamdani and Tsukamoto FIS, in which constituents used to form the consequents are an output MF (Jang 1993), to explore whether such models could generate significantly improved results.

Research Method

Although risk management and risk allocation may vary from risk to risk and from project to project, the mechanism that dominates the risk allocation decision-making process with regard to different risks remains the same (Jin 2010a; Jin and Doloi 2008). Therefore, to follow the triangulation concept in academic research (Hammersley and Atkinson 2007) and facilitate a comparison of evaluation results between neuro-fuzzy models established in the current paper and MLR models in Jin's (2010a) work, the results regarding three risks are reported in this paper. The three selected risks are (1) defects in design in development stage (coded as RD); (2) demand below anticipation in operation stage (coded as RO); and (3) adverse changes in law, policy, or regulations during the lifecycle (coded as RL). They are selected for reporting because (1) they have been deemed controversial and problematic in terms of their allocation (Carrillo et al. 2006; Medda 2007; Ng and Loosemore 2007; Shen et al. 2006; Tiong 1990; Tiong 1995), and (2) they exist in different stages of the project lifecycle. Similar strategies have been adopted in previous research (e.g., Kangari and Riggs 1989).

To model the RADM process and accurately forecast efficient risk-allocation strategies, a neuro-fuzzy model was developed based on the framework and reported in the following section. Based on the framework, a questionnaire was designed for an industrywide survey. The questionnaire asked respondents to provide reliable information about a PPP project in which they had appropriate involvement and/or knowledge. The primary information requested included the evaluation of the characteristics of the aforementioned risk management service transaction, the adopted risk-allocation strategies, and the perceived most efficient risk-allocation strategies in the specified PPP projects. Respondents were also required to provide information about their PPP experience and designation.

A multitude of environmental uncertainty (EU) factors were identified by Jin (2010a, Table 2). However, uncertainties are usually correlated to one another (Winch 1989). Too many variables often cause the curse of dimensionality if they are directly taken as input variables into a model (Hines 1997). Therefore, a fuzzy operation framework was developed to obtain an indicator to index EU, for which the importance weight (EUIW) and the rating (EUR) of each qualitative EU factor were considered as linguistic variables. The EUIWs and the EURs, respectively, were established based on the evaluation by a panel of experts and obtained in the questionnaire survey. A fuzzy arithmetical operation was then employed to aggregate the fuzzy numbers into an EU index (EUI), which was taken as an input variable in the neuro-fuzzy model. This approach, known as fuzzy weighted average (FWA) operation, has been applied in many multicriteria decision-making studies (e.g., Schmucker 1984; Tah and Carr 2000; Ngai and Wat 2005; Li et al. 2007).

In this study, a panel of five experts was invited to evaluate the EUIWs. The Delphi procedure was used for eliciting the consented opinions of the panel. The questionnaire for the consultation was sent forward and back through e-mail to ensure anonymity among the panelists and disseminated for three rounds to achieve appropriate iteration. Between each consecutive round of questionnaire iteration, the panelists were presented with the median values of the group response for further consideration. The median value of the evaluation in the final round was taken as the group judgment. The profile of the panelists is shown in Table 1. Their evaluation is deemed reliable. Additionally, these experts were also asked to respond to the survey questionnaire. The information in their responses was taken as the test data set for model testing.

Following a pilot survey during a PPP workshop and consequent refinement of the questionnaire, an industrywide questionnaire survey was carried out in Australia. The target population of the survey was all the professionals and decision makers from both public and private sectors who have been involved in the risk management of PPP projects in Australia. Judgmental or purposive sampling was used, in which a sample is drawn using judgmental selection procedures (Tan 2004). The strategy for sample selection was first to identify PPP infrastructure projects in Australian market, then to identify major partners of the identified projects, and finally to identify professionals and decision makers in major partners' organizations from public domain. In total, 386 questionnaires were distributed, and 44 useful responses were received. The survey response rate of 11.4%, though not high, is acceptable for a survey of this nature (De Vaus 2001). The profile of the respondents is shown in Table 2. They were deemed appropriate to provide reliable response to the survey because of their ample experience in PPP projects and in the construction industry. Meanwhile, the same questionnaire was distributed to the previously discussed expert panel. The data set obtained from the five experts was used as a test data set for model evaluation. The returned questionnaires were checked and edited to ensure completeness and consistency. The entire process, including model development, training, and evaluation, was carried out using the R2007b version of MATLAB software on the Windows XP platform in a PC environment.

Table 1. Profile of Expert Panelists

Panelists	Designation	Affiliation	Experience in construction industry	Experience in PPPs
1	Director	Contractor	36 years	12 projects
2	Senior partner	Consultant	28 years	16 projects
3	Partner	Consultant	23 years	10 projects
4	General manager	Contractor	25 years	8 projects
5	Project director	Public client	25 years	18 projects

Table 2. Profile of Survey Respondents (Jin 2010a)

Item	Category	Frequency	Percentage
Respondents' designation	Senior level	41	93.2
	Mid level	3	6.8
	Junior level	0	0.0
Respondents' experiences in construction industry	≤ 5 years	0	0.0
	5–10 years	14	31.8
	10–20 years	13	29.6
	20–30 years	10	22.7
	> 30 years	6	13.6
	Unknown	1	2.3
Respondents' experiences in PPP projects	None	0	0.0
	1–2 projects	10	22.7
	3–5 projects	10	22.7
	6–10 projects	16	36.4
	> 10 projects	8	18.2

Construction of Neuro-Fuzzy Model

A neuro-fuzzy system usually involves a structure learning and parameter learning. A neuro-fuzzy model was thus proposed for combining structure and parameter learning into a common framework (Jin 2010b). To initiate the learning process in the neuro-fuzzy model, domain knowledge about input and output variables and a set of input/output data were obtained through literature review and a questionnaire survey, respectively. The learning process was then implemented in two sequential learning modules, the structure learning module (SLM) and the parameter learning module (PLM) (see Fig. 2). By generating fuzzy rules from and adjusting parameters based on the numerical data obtained in the fieldwork, the neuro-fuzzy model was able to realize the synthetic benefits associated with neural networks and fuzzy logic. In the ensuing subsections, these two learning modules are described and illustrated by using an example case where appropriate.

Structure Learning Module

The tasks in the SLM are to determine input and output variables based on domain knowledge and to generate a set of fuzzy if-then rules from the input/output data set. These variables and fuzzy rules were then used to determine the structure of the PLM in the neuro-fuzzy model.

Determining Input and Output Variables

The input and output variables are adapted from the independent and dependent variables established in a recent study (Jin 2010a). In particular, the difference of input variable (IV) should be noted in the current paper, as opposed to independent variable in the other paper (Jin 2010a). The IVs of the neuro-fuzzy model include RM routine (asset specificity) (IV_1), partners' cooperation history (IV_2), public partner's RM commitment (IV_3), private partner's RM commitment (IV_4), environmental uncertainty (IV_5), and partner's RM capability superiority (IV_6). IV_1 was assessed by a set of three fuzzy values, i.e., low (L), medium (M), and high (H). IV_2 through IV_5 were assessed by a set of two fuzzy values, i.e., low (L) and high (H). IV_6 was assessed by a set of two fuzzy values, i.e., the public partner's capability is superior (public) and the private partner's capability is superior (private). The reason that only IV_1 was assessed by a set of three fuzzy values is that asset specificity

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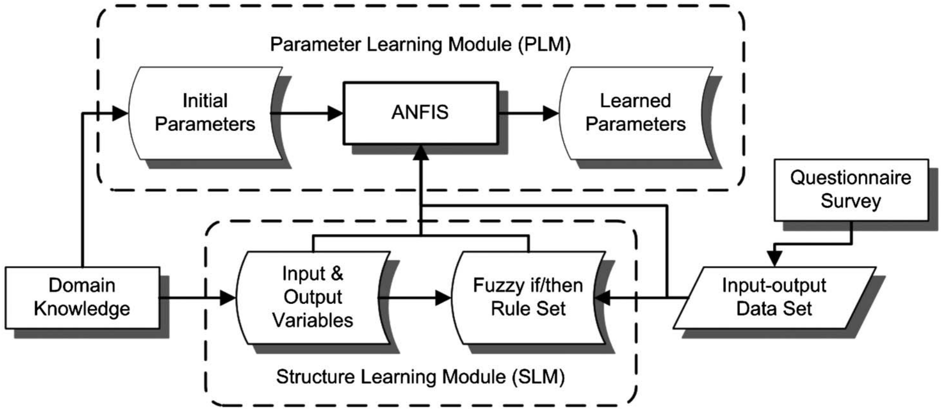

Fig. 2. General structure of neuro-fuzzy model

increases the transaction costs of all forms of governance and thus is the principal factor in explaining TCE (Williamson 1996). Therefore, the status of asset specificity receives more detailed attention and analysis (Jin 2010a; Jin and Doloi 2008).

IV_1 and IV_2 were evaluated on a five-point Likert scale directly by the respondents in the survey. IV_3 and IV_4 were derived from the respondents' evaluation of the corresponding observed variables in the survey by using principal component analysis. IV_5 was derived from the respondents' evaluation of the corresponding EU factors in the survey by applying fuzzy operation. IV_6 is the RM capability difference between public and private partners and measured by the difference of partner's RM mechanisms. The Partner's RM mechanism was derived from the respondents' evaluation of the corresponding observed variables in the survey by using principal component analysis. A detailed discussion on the operationalization of the framework is provided in Jin (2010a) and will not be repeated here.

Each fuzzy value is a fuzzy set and determined by a membership function. The commonly used MFs include Gaussian functions, triangular functions, and trapezoidal functions (Lin and Lee 1996). In this study, the Gaussian function was adopted because it is good at achieving smoothness (MathWorks 2007) and can avoid the problem of having zero in the denominator in a MF (Liu and Ling 2005). It has been applied in a number of similar studies on construction-related topics (e.g., Liu and Ling 2005). The symmetric Gaussian function, which depends on parameters σ and c, can be defined as

$$\mu(x;\sigma,c) = e^{[-(x-c)^2]/(2\sigma^2)} \tag{1}$$

where σ and c determine the width and center of the MFs, respectively.

The MFs and the initial values of parameters of the IVs are shown in Table 3. The values of the parameter σ were set in such a way that $\mu(x) = 1.0$ when $x = \sigma$. The values of the parameter c were set in such a way that the MFs satisfy the condition of ε-completeness (Lee 1990) with $\varepsilon = 0.5$. This means that given a value x of one of the inputs in the operating range, a linguistic value A can always be found such that $\mu_A(x) \geq \varepsilon$.

The output variable (OV) of the neuro-fuzzy model is the risk-allocation strategy. The OV's possible value $f \in \{1,2,3,4,5\}$, where $\{1,2,3,4,5\}$ represents a five-point scale of risk transfer proportion, which ranges in a continuum from 1, denoting full bearing by the public partner, via 3, denoting equal bearing by the public and private partners, to 5, denoting full bearing by the private partner. Because the first-order Sugeno-type FIS was used in the neuro-fuzzy model, the total number of MFs of OV is the same as that of fuzzy if-then rules, which were obtained using the method that is presented in the following subsection. MFs of OV take the form of $f_i = p_i x_1 + q_i x_2 + r_i x_3 + s_i x_4 + t_i x_5 + u_i x_6 + v_i$, where i indexes fuzzy if-then rules; and $\{p_i, q_i, r_i, s_i, t_i, u_i, v_i\}$ is the consequent parameter set of the ith fuzzy if-then rule. Before passing to the PLM, each set of consequent parameters was initialized based on the target output value of a corresponding data pair. The constant v_i was assigned with the target output value, and

Table 3. Fuzzy Values and Membership Functions of Input Variables

Variable	Code	Value	Initial membership function $\mu(x;\sigma,c)$
RM asset specificity (IV_1)	H	High	$e^{[-(x-5)^2]/[2(0.85)^2]}$
	M	Medium	$e^{[-(x-3)^2]/[2(0.85)^2]}$
	L	Low	$e^{[-(x-1)^2]/[2(0.85)^2]}$
Partners' cooperation history (IV_2)	H	High	$e^{[-(x-5)^2]/[2(1.7)^2]}$
	L	Low	$e^{[-(x-1)^2]/[2(1.7)^2]}$
Public partner's RM commitment (IV_3)	H	High	$e^{[-(x-5)^2]/[2(1.7)^2]}$
	L	Low	$e^{[-(x-1)^2]/[2(1.7)^2]}$
Private partner's RM commitment (IV_4)	H	High	$e^{[-(x-5)^2]/[2(1.7)^2]}$
	L	Low	$e^{[-(x-1)^2]/[2(1.7)^2]}$
Environmental uncertainty (IV_5)	H	High	$e^{[-(x-5)^2]/[2(1.7)^2]}$
	L	Low	$e^{[-(x-1)^2]/[2(1.7)^2]}$
Capability superiority (IV_6)	Private	Private partner's capability is superior	$e^{[-(x-4)^2]/[2(3.4)^2]}$
	Public	Public partner's capability is superior	$e^{\{-[x-(-4)]^2\}/[2(3.4)^2]}$

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the other parameters were assigned with zero as their initial value. Taking the first case of the 44 survey responses (Case 1) with regard to R_L as an example, because the target output value in Case 1 is 4, the consequent parameter set is $\{0, 0, 0, 0, 0, 0, 4\}$.

Generating Fuzzy Rule Set

Identified concise rules can provide an initial structure of networks so that learning processes can be fast, reliable, and highly intuitive (Kim and Kasabov 1999). In this study, a simple and straightforward method for generating fuzzy rules from a numerical input/output data set was used. It avoids the time-consuming training, which is typically required for neural network–based methods. It is also easy to update or modify the fuzzy rule set by creating a new rule for a new input/output data pair. This method was adapted from the one that was proposed by Wang and Mendel (1992) and consists of three steps, as follows.

Step 1. Determine the membership values of each input value of a given data pair for all fuzzy values of the corresponding fuzzy variable. In Case 1, the input/output data pair is (1.0, 2.0, 4.0, 4.7, 3.0, 1.0, and 4.0), where the first six and the last numbers are input and output values, respectively. The outcome of the Step 1 calculation is shown in the "Membership value" column in Table 4.

Step 2. Assign each input value with a fuzzy value that the input value has the maximum membership value of. In Table 4, the maximum membership value for each fuzzy variable is highlighted in bold. It can be observed that in Case 1, the fuzzy values assigned to the input values of IV_1 through IV_6 are high, low, high, high, low, and public, respectively. If two membership values are the same for an input value, the corresponding input/output data pair will be duplicated, and this input value will be assigned with one fuzzy value in the original data pair and with the other in the duplicated data pair. This means the data set will be expanded to include ambiguous cases.

Step 3. Obtain one rule from each input/output data pair. In Case 1, the rule was obtained as

If IV_1 = high, and
IV_2 = low, and
IV_3 = high, and
IV_4 = high, and
IV_5 = low, and
IV_6 = public,
Then the OV is $f_1 = p_1 \times 1.0 + q_1 \times 2.0 + r_1 \times 4.0 + s_1 \times 4.7 + t_1 \times 3.0 + u_1 \times 1.0 + v_1 = 4$

Table 4. Determining the "If" Part of a Fuzzy If-Then Rule Based on Input Values of the Case

Fuzzy variable	Numerical value of input data	Membership value (fuzzy value)	Assigned fuzzy value
IV_1	1.0	1.000 (high)	High
		0.063 (medium)	
		0.000 (low)	
IV_2	2.0	0.211 (high)	Low
		0.841 (low)	
IV_3	4.0	0.841 (high)	High
		0.211 (low)	
IV_4	4.7	0.981 (high)	High
		0.098 (low)	
IV_5	3.0	0.494 (high)	Low
		0.508 (low)	
IV_6	1.0	0.675 (public)	Public
		0.341 (private)	

If two or more generated fuzzy rules shared the same if-part and then-part (in terms of target output value), they were combined and only one rule was generated. If two or more generated fuzzy rules shared the same if-part but a different then-part (in terms of target output value), they were retained and equally weighted in the PLM.

By using this approach, 48, 53, and 41 rules were identified for R_D, R_O, and R_L, respectively.

Parameter Learning Module

After the input and output variables have been determined and the fuzzy rules obtained, the structure of the neuro-fuzzy learning model can be established. The neuro-fuzzy model thus enters into the PLM. The PLM was designed to tune MFs by adjusting antecedent and consequent parameters to achieve a desired level of system performance. The task was accomplished by building and training an ANFIS. The architecture of an ANFIS both approximates the fuzzy reasoning of a Sugeno FIS and facilitates learning from the input/output data set. The learning algorithm of ANFIS integrates the advantages of gradient-descent optimization and LSE methods. The architecture and learning algorithm of the PLM, which is an ANFIS, are described in the following subsections.

Architecture of ANFIS

The proposed ANFIS in the neuro-fuzzy model is a first-order Sugeno-type FIS based on a multilayer neural network. It has five hidden layers in addition ot input and output layers. In the hidden layers, nodes function as MFs and fuzzy rules. This boasts an advantage that a conventional feedforward multilayer neural network lacks, which is that hidden layers are usually difficult to interpret and/or modify. The architecture of the proposed ANFIS is illustrated in Fig. 3, in which a square was used to represent an adaptive node whose function depends on its parameter values, and a circle was used to denote a fixed node that has an empty parameter set and a fixed function. The features and functions of each layer are presented as follows.

Input layer. Nodes in the input layer are input nodes that represent crisp input values. Accordingly, the input value of the kth IV is denoted by x_k, where $k \in \{1, 2, \ldots, 6\}$ (i.e., six IVs). Each node in this layer is only connected to the nodes that represent the MFs of the corresponding fuzzy values of the associated IVs in the next layer, i.e., Layer 1. The nodes in this layer thus only transmit input values to the corresponding nodes in Layer 1.

Layer 1. Nodes in Layer 1 are adaptive square nodes labeled F_j^k and act as MFs that define the fuzzy values of IVs. Input values (i.e., x_k) are fed to this layer. The outputs of this layer are thus the membership values of the crisp input values x_k. The Gaussian function was taken as MFs with σ and c as the parameter set. Parameters in this layer are referred to as antecedent parameters. Therefore, the output of a node in Layer 1 is defined by

$$O_j^{(1),k} = e^{[-(x_k - c_j^k)^2]/2\sigma_j^{k2}} \quad (2)$$

where σ_j^k and c_j^k = parameters of the MF that represent the lth fuzzy value of the kth IV; (1) denotes Layer 1; $k \in \{1, 2, \ldots, 6\}$ (i.e., six IVs); and $j \in \{1, 2, 3\}$ if $k = 1$ and $j \in \{1, 2\}$ if $k \in \{2, 3, 4, 5, 6\}$ (i.e., three and two fuzzy values of the first and the other IVs, respectively). The initial connection weights were set to unity. As the value of these parameters changed during training, the form of the corresponding MFs varied.

Layer 2. Every node in this layer is a fixed circle node labeled Π, which represents the if-part of a fuzzy rule. That is, each node in Layer 2 is only connected with those nodes in Layer 1 that represent the MFs of the fuzzy values specified in the if-part of the corresponding fuzzy rule. Incoming signals were multiplied,

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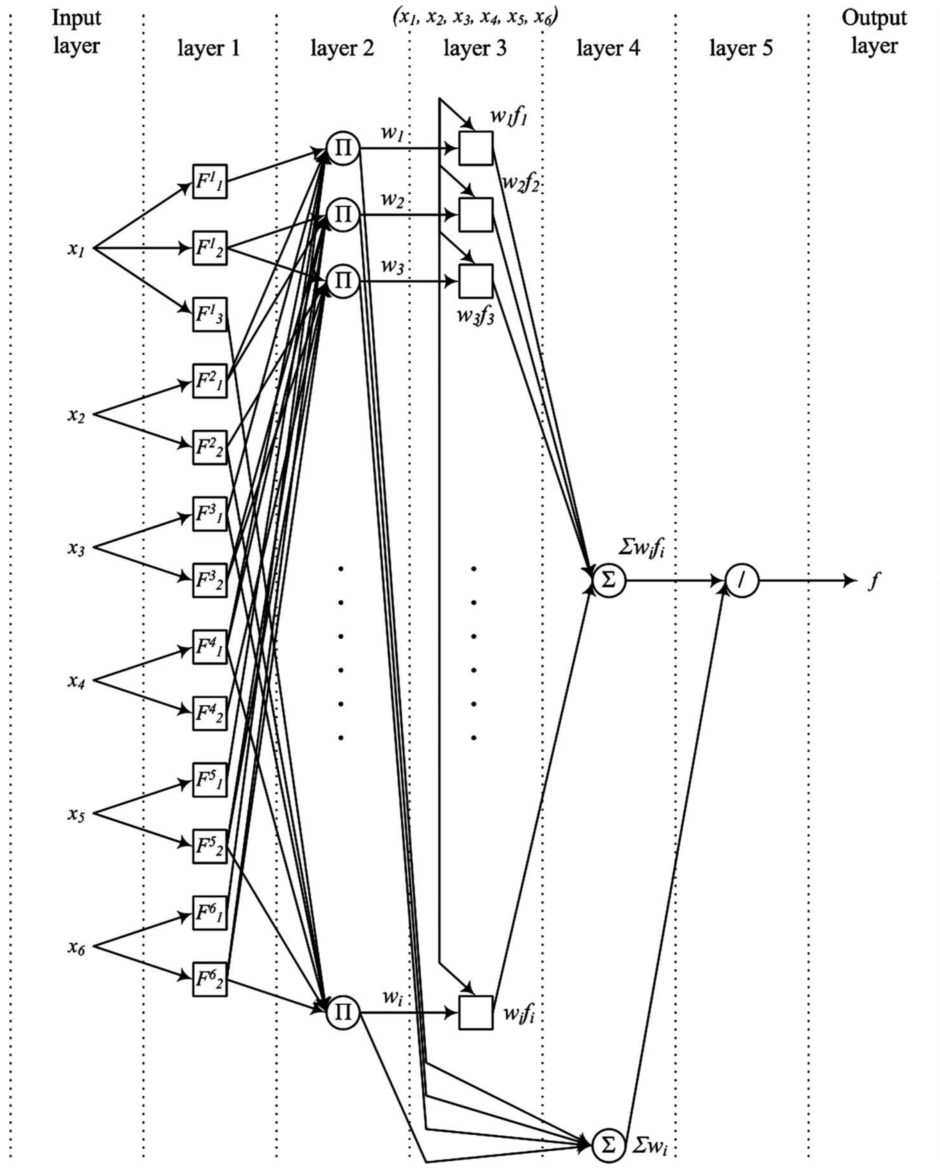

Fig. 3. ANFIS architecture

and the corresponding products were taken as the outputs of Layer 2, which are defined by

$$O_i^{(2)} = \prod_{k=1}^{6} O_j^{(1),k} \tag{3}$$

where (2) denotes Layer 2; i = index of fuzzy rules; and $i \in \{1, 2, \ldots, n\}$, where n = number of the fuzzy rules that were generated in the SLM. The output of each node represents the firing strength of a rule. The initial connection weights were set to unity. Thus, all the nodes in Layer 2 form the fuzzy rule set.

Layer 3. Every node in this layer is an adaptive square node, with the node output defined by

$$O_i^{(3)} = w_i f_i = O_i^{(2)}(p_i x_1 + q_i x_2 + r_i x_3 + s_i x_4 + t_i x_5 + u_i x_6 + v_i) \tag{4}$$

where w_i = firing strength of a fuzzy rule, i.e., $O_i^{(2)}$; and f_i = then-part of a fuzzy rule, i.e., a first-order polynomial of the input values. Parameters in this layer, i.e., $\{p_i, q_i, r_i, s_i, t_i, u_i, v_i\}$, are referred to as consequent parameters. Each node in Layer 3 is fully connected with the nodes in the input layer and only connected with one node in Layer 2, according to the corresponding rule.

Layer 4. There are two nodes in this layer. One node calculates the sum of the outputs of all nodes in Layer 3 and is thus fully connected with the nodes in Layer 3. Its output is defined by

$$\begin{aligned} O_1^{(4)} &= \sum_i w_i f_i = \sum_i O_i^{(3)} \\ &= \sum_i O_i^{(2)}(p_i x_1 + q_i x_2 + r_i x_3 + s_i x_4 + t_i x_5 + u_i x_6 + v_i) \end{aligned} \tag{5}$$

The other node calculates the sum of all the rules' firing strengths and is thus fully connected with the nodes in Layer 2. Its output is defined by

$$O_2^{(4)} = \sum_i w_i = \sum_i O_i^{(2)} \tag{6}$$

Layer 5. The single node in this layer is a fixed circle node labeled with a slash (/), and it computes the overall output as the ratio of the output of the first node to that of the second node in Layer 4. The node output is defined by

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$$O_1^{(5)} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} = \frac{O_1^{(4)}}{O_2^{(4)}} \qquad (7)$$

where $\overline{w_i}$ = normalized firing strength.

Output layer. The single node in the output layer only receives the output of Layer 5 and takes it as the final output of the ANFIS. The output variable is the risk-allocation strategy.

Parameter Learning Algorithms

Once the ANFIS was established, it was used to tune the antecedent and consequent parameters. There are a number of algorithms suitable for parameter learning through adjusting the parameters of MFs. The most commonly used learning algorithms are based on gradient descent (Horikawa et al. 1992; Hung 1993; Kasabov et al. 1997; Kim and Kasabov 1999; Lin and Lee 1991; Shann and Fu 1995). Because ANFIS was adopted in PLM, a hybrid learning algorithm developed by Jang (1993), which uses a gradient descent–based back-propagation algorithm and a least squares estimator algorithm to optimize the antecedent and consequent parameters, respectively, was applied directly to the PLM. To apply the hybrid learning algorithm, each training epoch was composed of a forward pass and a backward pass. A detailed explanation of the gradient descent–based BP algorithm and LSE algorithm is beyond the scope of this study. Please refer to the cited works for complete coverage on the related topics.

Training of Neuro-Fuzzy Model

In this study, the real project-based data sets obtained in the survey and from the expert panel were deemed as a training set and a test set, as shown in Tables 5 and 6, respectively. The training set was further partitioned into two disjoint subsets, i.e., the estimation subset used for model selection and the validation subset used for model validation. The objectives were to (1) assess the performance of various candidate models and select the best one by validating the model on the validation subset, which is different from the estimation subset; and (2) guard the selected model against the possibility of overfitting the validation subset by measuring the generalization performance of the selected model on the test set, which is different from the validation subset (Haykin 1999).

The dilemma of a learning system is how to remain adaptable enough to learn new things and yet remain stable enough to preserve learned knowledge. To tackle this problem, the beginning of overfitting was identified by using early stopping training method (Amari et al. 1995b). The training session was stopped in each epoch and the network was then tested on the validation subset. This process was repeated until the initially monotonically decreasing learning curve for validation started to increase constantly. The early stopping training method has been proved capable of improving the generalization performance of the network over exhaustive training (Amari et al. 1995a).

In this study, the available data set was limited due to the relatively small number of PPP projects. The multifold cross-validation method may thus be used (see Haykin 1999, p. 218). An extreme form of multifold cross-validation, known as the leave-one-out method, was used in this study. In detail, 43 (i.e., 44 − 1) data pairs were used to train the model, and the model was validated on the single data pair left out. The process was repeated 44 times. For each iteration, a different data pair was left out for validation. The root-mean-squared error (RMSE) under estimation and validation was then averaged over the 44 rounds of training, which are denoted by $\mathrm{RMSE}_{\mathrm{est.}}^{\mathrm{avg.}}$ and $\mathrm{RMSE}_{\mathrm{val.}}^{\mathrm{avg.}}$, respectively. The RMSE is defined as

Table 5. Project Profile in Training Data Set (Including Estimation and Validation)

Item	Category	Frequency	Percentage
Project value	AU$ ≤ 100 m	6	13.6
	100 m < AU$ ≤ 250 m	16	36.4
	250 m < AU$ ≤ 500 m	8	18.2
	500 m < AU$ ≤ 1000 m	4	9.1
	AU$ > 1,000 m	10	22.7
Concession period (year)	Years ≤ 5	0	0.0
	5 < years ≤ 10	2	4.5
	10 < years ≤ 20	3	6.8
	20 < years ≤ 30	29	66.0
	Years > 30	10	22.7
PPP type	Design-build-finance-operate (DBFO)	18	40.9
	Build-own-operate-transfer (BOOT)	18	40.9
	Design-build-finance-manage (DBFM)	5	11.4
	Build-operate-transfer (BOT)	2	4.5
	Build-own-operate (BOO)	1	2.3
Infrastructure sector	Energy	0	0.0
	Hydraulic services	2	4.6
	Transport	13	29.5
	Information and communication technology	1	2.3
	Health	12	27.2
	Housing	3	6.8
	Education	5	11.4
	Justice and prison	6	13.6

Table 6. Project Profile in Evaluation (or Test) Data Set

Item	Category	Frequency	Percentage
Project value	AU$ ≤ 100m	1	20.0
	100 m < AU$ ≤ 250 m	2	40.0
	250 m < AU$ ≤ 500 m	1	20.0
	500 m < AU$ ≤ 1,000 m	1	20.0
Concession	10 < years ≤ 20	1	20.0
Period (year)	20 < years ≤ 30	4	80.0
PPP type	Design-build-finance-operate (DBFO)	3	60.0
	Build-own-operate-transfer (BOOT)	2	40.0
Infrastructure sector	Transport	2	40.0
	Health	2	40.0
	Education	1	20.0

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(x_i - t_i)^2}{n}} \qquad (8)$$

where x_i = risk-allocation strategy in the ith case forecasted by the neuro-fuzzy model; t_i = suggested efficient risk-allocation strategy

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Table 7. Training Results of Neuro-Fuzzy Model

Risk	$RMSE^{avg.}_{est.}$	$RMSE^{avg.}_{val.}$
R_D	0.0998	0.1893
R_O	0.0498	0.0433
R_L	0.0035	0.0098

in the ith case; and n = number of cases, which is 44. The training results are presented in Table 7.

Validation of Neuro-Fuzzy Model

To evaluate the performance of the neuro-fuzzy model, the results based on the test data set when using the neuro-fuzzy model were compared with those using the MLR technique (see Jin 2010a) and FIS models (see Jin and Doloi 2009). The test data set (which can also be referred as the evaluation or validation data set) was obtained from the expert panel, the profile of which is reported in Table 1, and is based on the information of five real PPP projects, the profiles of which are reported in Table 6. To allow comparison, a set of performance indexes were used, which include mean percentage error (MPE), mean absolute percentage error (MAPE), and RMSE. These performance indexes have been adopted in many previous research works (e.g., Jang 1993; Soetanto and Proverbs 2004; Liu and Ling 2005). RMSE has been defined previously. The other two performance indexes are defined as follows:

$$\mathrm{MPE} = \sum_{i=1}^{n} \frac{T_i - O_i}{T_i} \times 100\%/n \tag{9}$$

$$\mathrm{MAPE} = \sum_{i=1}^{n} \left| \frac{T_i - O_i}{T_i} \times 100\% \right| /n \tag{10}$$

where $n = 5$, which is the number of testing data pairs; and T_i and O_i = ith target output and calculated output, respectively.

The ratings of the six IVs for each case were fed into the set of trained neuro-fuzzy models and the established FIS models (see Jin and Doloi 2009). The ratings of the identified independent variables for each case were fed into the set of established MLR models (see Jin 2010a). The forecasted efficient risk-allocation strategies by the models were compared with the specified efficient risk-allocation strategies by the interviewees.

The results of model evaluation are shown in Table 8. Regarding each risk in question, the lowest value of each performance index is highlighted in bold. In Table 8, regarding all three risks under analysis, the outcome is that the neuro-fuzzy models have achieved a significant improvement in RMSE, MPE, and MAPE compared with the MLR and FIS models. Taking R_D as an example, the neuro-fuzzy model may generate an error of ± 0.0671 on average, may have the propensity to overforecast a bit ($+0.3007\%$), and may contain 1.6621% error in the forecast on average. In comparison, the MLR and FIS models may, respectively, generate an error of ± 0.5211 and ± 0.4461 on average, may have the propensity to underforecast by -11.9190 and -9.8760%, and may contain 32.3232 and 29.8920% error in the forecast on average. That is to say, for instance, when an efficient risk-allocation strategy for R_D is supposed to be equally shared by partners (or 3 on a five-point Likert scale), the relevant neuro-fuzzy model generally gives an accurate forecast, but the relevant MLR and FIS models may suggest "shared by partners but either public or private partner take a much higher portion of the risk" (2 or 4 on a five-point Likert scale). Given the subjective nature of the judgments by the respondents and interviewees, it can be concluded that the developed neuro-fuzzy models are valid and robust and have better captured the essential components of the underlying nonlinear and uncertain dynamics than the MLR and FIS modeling approaches.

Table 8. Comparison of Evaluation Results among Neuro-Fuzzy, MLR and FIS Models

			Risks	
Perf. Index	Model	R_L	R_O	R_D
RMSE	Neuro-fuzzy	**0.1113**	**0.0312**	**0.0671**
	MLR	0.7428	0.3580	0.5211
	FIS	0.3649	0.4373	0.4461
MPE (percentage)	Neuro-fuzzy	**2.2728**	**−0.7217**	**0.3007**
	MLR	−19.7632	−20.4199	−11.9190
	FIS	−11.7053	−23.1400	−9.8760
MAPE (percentage)	Neuro-fuzzy	**2.7400**	**2.0850**	**1.6621**
	MLR	31.9375	23.3132	32.3232
	FIS	14.9613	33.7000	29.8920

Note: The lowest value in each category is highlighted in bold.

Application of Neuro-Fuzzy Model

The established neuro-fuzzy model is applied to the process of forecasting an efficient risk-allocation strategy for defects in design risk (R_D) of the New Schools PPP Project (Project 1) (referred to as the project hereafter) in Sydney, New South Wales (NSW), Australia. The project was the first project delivered under the NSW government program "Working with Government: Guidelines for Privately Financed Projects" (NSW Audit Office 2006). It was also the first privately financed social infrastructure project in NSW and the first privately financed schools project in Australia (NSW Treasury 2005). The project commenced in 2000 with investigations by the Department of Education and Training (DET) on the feasibility of packaging schools delivery as a privately financed project. The project then progressed to the expression of interest phase in October 2001, moving through a request for detailed proposals and best and final offer before financial close was achieved in March 2003 (NSW Treasury 2005).

The private sector financed, designed, and constructed nine new public schools in new urban release areas in northwestern and western Sydney, and in two other NSW regions, the Illawarra and the Central Coast. Four schools opened in 2004 and five opened in 2005. Additionally, the private sector will provide cleaning, maintenance, security, safety, utility, furniture, equipment and grounds maintenance, and other services for these school buildings until December 31, 2032, when the buildings will be handed over to DET in return for performance-based monthly payments by the DET during the operational phase of the project (NSW DET 2003).

The tasks of the project were carried out by Axiom Education Pty. Ltd. (contractor), supported by ABN AMRO Australia Limited (bond manager), Hansen Yuncken Pty. Ltd. (construction contractor), St. Hilliers Contracting Pty. Ltd. (construction contractor), and Spotless Services Australia Ltd. (operator) (NSW DET 2003). The project was able to deliver better value-for-money as tested against the public sector comparator. The risk-adjusted cost of private sector delivery over the 30-year life of the project was AU$131.4 million. The project's savings were measured against the most likely scenario for public sector delivery (AU$141.8 million), producing an estimated saving of just over 7%.

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Table 9. Application of Neuro-Fuzzy Model to a Real Project—Variables and Their Values

Variable	Value
Level of RM asset specificity	High
Level of RM transaction frequency	Low
Level of public partner's RM commitment	High
Level of private partner's RM commitment	Medium
Level of public partner's RM capability	Medium
Level of private partner's RM capability	Medium
Level of environmental uncertainty	Medium
Efficient risk-allocation strategy	Transfer none or little of the risk

After relevant data had been collected, the neuro-fuzzy model proceeded by running the imbedded programs. The input and output variables of the neuro-fuzzy model and their values are presented in Table 9. These variables are presented in linguistic values rather than numeric values so that the imprecision and uncertainty intrinsic in language can be addressed. Table 9 shows that the collaboration history between the two partners is not long. The private partner needed to invest in highly specific assets to manage the design risk. Both partners' capability to tackle the design risk was medium. However, neither sector was unwilling to manage the risk, probably because the general environment for managing the risk is not highly uncertain. In particular, the public partner was holding a high commitment to managing the risk. Under such circumstances, transferring design risk to the contractor would result in a higher price to manage the risk and even create additional significant risks for both parties.

Table 9 also shows that the efficient risk-allocation strategy forecasted by the neuro-fuzzy model suggests that government bear most or all of the design risk. This is exactly the strategy that was adopted in the project. That is, the proportion of design risk transferred to the private sector was relatively low (NSW Audit Office 2006). There was an expectation that the private sector would introduce innovative solutions to reduce the whole of life cost of the schools. In reality, this was not reflected in the development process of the project. Only the current school buildings specifications were observed, which had been set as the minimum requirement by the DET. The DET's specifications detailed the required school facilities room by room, including size requirements, finishes, number of power outlets, and others (NSW DET 2003). The DET saw these specifications as ensuring that the provision of school facilities remains equitable (NSW Treasury 2005). Because they are subject to regular reviews to achieve efficiency in design, innovation, and cost effectiveness, they provide greater certainty in relation to the final product. Therefore, there was little innovative design in the way. The recent audit report thus found that the DET clearly defined its requirements from the outset and scoped the project to maximize its prospects of achieving value for money (NSW Audit Office 2006).

Conclusion

Risk allocation plays a critical role in PPP infrastructure projects. Project success (or failure) is contingent on whether the adopted risk-allocation strategy can lead to efficient risk management (or not). In this paper, based on Jin's (2010a) recent work, a theoretical framework was developed to model the process of RADM in PPP infrastructure projects by drawing on the transaction cost economics and the resource-based view of organizational capabilities. To test whether the framework is valid for its designed purpose, the ANN technique was integrated into an FIS to build a neuro-fuzzy model, which is adapted from an ANFIS, to forecast efficient risk-allocation strategies in PPP infrastructure projects. The neuro-fuzzy approach was chosen because it combines the strengths of fuzzy logic and ANN and thus possesses strong learning ability and the capability to handle unspecificity, uncertainty, nonlinearity, and complexity.

The learning process of the neuro-fuzzy model was implemented in two sequential learning modules, which are the SLM and the PLM. The tasks in the SLM were to determine input and output variables based on domain knowledge and to generate a set of fuzzy if-then rules from the input/output data set. The IVs of the neuro-fuzzy model included RM asset specificity (IV_1), partners' cooperation history (IV_2), public partner's RM commitment (IV_3), private partner's RM commitment (IV_4), environmental uncertainty (IV_5), and partner's RM capability superiority (IV_6). The OV was the efficient risk-allocation strategy. These variables and fuzzy rules were then used to determine the structure of the PLM. The PLM was designed to tune membership functions by adjusting antecedent and consequent parameters to achieve a desired level of system performance. The task was accomplished by building and training an ANFIS, which integrates the advantages of the gradient-descent back-propagation optimization and the least-squares estimator methods.

To train the neuro-fuzzy model, real project-based data about risk allocation in PPP infrastructure projects were collected in an industrywide survey in Australia for model estimation and validation. By using the early stopping and the leave-one-out training methods to ensure generalizability, the neuro-fuzzy models were trained on a relatively small data set. Meanwhile, another real project-based data set for model evaluation and validation was elicited from an expert panel comprising five panelists. To evaluate the performance of the neuro-fuzzy models, the performance of corresponding MLR and FIS models, which were established in previous studies, were used for a comparison. Model testing results show that the performance of the neuro-fuzzy models in terms of MPE, MAPE, and RMSE is much better than that of the MLR and FIS models. Given the subjective nature of the judgments by the respondents and interviewees, it was concluded that the neuro-fuzzy model is valid and robust and has better captured the essential components of the underlying nonlinear and uncertain dynamics.

With the tested model based on the TCE and the RBV theories and using neuro-fuzzy techniques, the risk allocation decision-making process in PPP infrastructure projects was successfully modeled and efficient risk-allocation strategies were accurately forecasted. This paper presents a significant contribution to the body of knowledge because the established neuro-fuzzy model for efficient risk allocation represents an innovative and successful application of neuro-fuzzy techniques. It is thus possible to accurately predict efficient risk-allocation strategies in an ever-changing business environment, which had not been achieved in previous studies. This neuro-fuzzy model is expected to help industrial professionals make informed and calculated decisions on efficient risk allocation by forecasting optimal risk-allocation strategies. With various risks allocated to partners in a cost-efficient way, partners are getting closer to achieving successful risk management and the ultimate project triumph.

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