Neurofuzzy Decision Support System for Efficient Risk Allocation in Public-Private Partnership Infrastructure Projects

Xiao-Hua Jin[1]

Abstract: The performance of public-private partnership (PPP) infrastructure projects is largely contingent on whether the adopted risk allocation (RA) strategy is efficient. Theoretical frameworks drawing on the transaction cost economics and the resource-based view of organizational capability are able to explain the underlying mechanism but unable to accurately forecast efficient RA strategies. In this paper, a *neurofuzzy decision support system* (NFDSS) was developed to assist in the RA decision-making process in PPP projects. By combining fuzzy and neural network techniques, a synthesized fuzzy inference system was established and taken as the core component of the NFDSS. Evaluation results show that the NFDSS can forecast efficient RA strategies for PPP infrastructure projects at a highly accurate and effective level. A real PPP infrastructure project is used to demonstrate the NFDSS and its practical significance.

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Introduction

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

However, evidence from projects worldwide shows that risks are not managed properly (Thompson and Perry 1992). Construction projects manifest more risks than do other industries (Han and Diekmann 2004). The complexity of arrangements and incomplete contracting nature of PPP projects have led to increased risk exposure for all the parties involved (Woodward 1995). A perception that privatization involves transfer of all risks to the private sector is still prevalent in many countries (Faulkner 2004). Sometimes risks will inevitably be allocated to the party least able to refuse them rather than the party best able to manage them, especially when the government maintains maximum competitive tension (Thomas et al. 2003). However, 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). It is thus suboptimal for government to either retain or transfer inappropriate risks (Arndt 1999).

Ongoing efforts have been made in seeking a risk allocation decision-making (RADM) mechanism to achieve optimal risk allocation (RA) in PPP projects (DFA 2005). Jin (2010) recently established a theoretical framework drawing upon the transaction cost economics (TCE) and the resource-based view (RBV) of organizational capabilities. In a logical and holistic way, the framework interprets the mechanism underlying the decision-making process of how to efficiently allocate a given risk. Optimum models have been obtained by using multiple linear regression (MLR) technique and important linearly bound determinants identified (Jin 2010).

Nonetheless, it was acknowledged that, for more accurate prediction purpose, the basically probability-oriented MLR is unable to identify all the factors necessary to reflect realistic situations (Jin 2010). Therefore, nonprobability-oriented techniques have been considered to tackle issues characteristic of uncertainty, unspecificity, complexity, and nonlinearity during the process of RADM. In this paper, the theoretical framework is first revisited briefly, followed by a justification of why using neurofuzzy modeling techniques. Then the four-stage development of a *neurofuzzy decision support system* (NFDSS) is presented, which serves to forecast efficient RA strategies from a number of alternatives and adopts a *synthesized fuzzy inference system* (SynFIS) as the model base. The theoretical framework is taken as the architecture of the kernel component of the NFDSS. The NFDSS is validated

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and demonstrated by using a real PPP infrastructure project. Finally, a conclusion is presented.

Theoretical Framework of Efficient RADM

Based on the TCE and the RBV of organizational capabilities, Jin (2010) proposed a theoretical framework for interpreting RA mechanisms in PPP projects. Choosing a RA strategy is actually viewed as a process of deciding the proportion of risk management (RM) responsibility between internal and external organizations based on a series of characteristics of risk management service transaction in question (Jin 2010). Because any issue that can be formulated as a contracting problem can be investigated to advantage in transaction cost economizing terms (Williamson 1985), RADM in PPP projects is suitable to be viewed from a TCE perspective. Besides, many features of PPPs, including incomplete contracting, long-term partnership, heavy investment into assets, complex uncertainty, etc., also ensure such suitability (Jin and Doloi 2008b). Jin (2010) also emphasized that both production and governance costs must be taken into account in any analysis adopting 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, organizational capability, which production costs are greatly contingent on Jacobides and Hitt (2005), should be taken into consideration when seeking efficient governance structure (Jin 2010). 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 (RMS) transaction can be categorized into (1) private partner's RM routines, which embody competence in carrying out RM activities and indicate that alternative uses could have been achieved without sacrificing productive value (reversely approximating to supplier's asset specificity of TCE); (2) partners' cooperation history (approximating to transaction frequency of TCE); (3) partners' RM commitment (reversely matching behavioral uncertainty of TCE); (4) RM environmental uncertainty (EU) (matching environmental uncertainty of TCE); and (5) partners' RM mechanism (approximating the organizational capability of RBV) [see the work of Jin (2010) for a detailed discussion]. Accordingly, a theoretical framework has been established, as shown in Fig. 1. For different combinations of the status of these characteristics, there exist different RA strategies for achieving efficiency (Jin 2010).

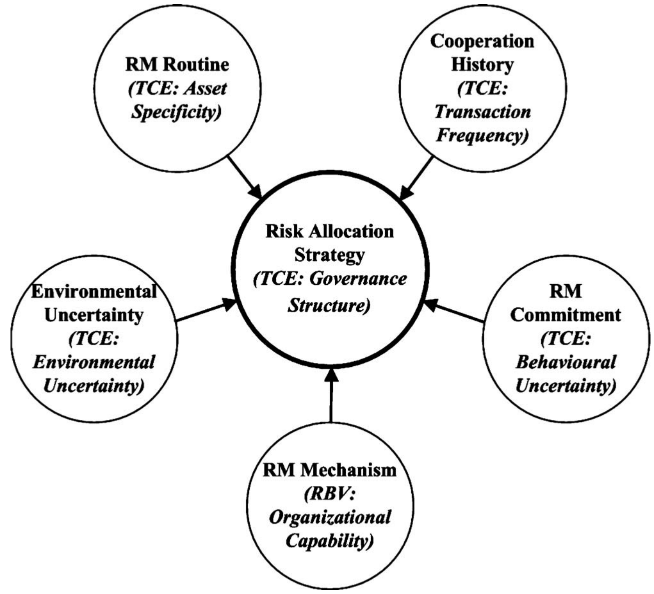

Fig. 1. Theoretical framework for RADM in PPP infrastructure projects (Jin 2010)

Neurofuzzy Modeling Techniques

The framework has been tested and generally supported by using MLR technique (Jin 2010). However, it cannot be used to accurately forecast efficient RA strategies due to the inherent limitations in MLR analysis. These limitations include only considering linear relationship, being probability oriented, and being unable to identify all the factors necessary to reflect realistic situations (Tsoukalas and Uhrig 1997). Therefore, nonprobability-based analysis techniques are required and nonlinear relationships need to be considered for accurately modeling RADM process (Jin and Doloi 2008b). One suitable approach is using *adaptive neurofuzzy inference system* (ANFIS), which combines the strengths of *fuzzy logic* (FL) and *artificial neural networks* (ANNs) and thus possesses the capability to handle unspecificity, uncertainty, nonlinearity, and complexity (Jang 1993; Jang and Sun 1995) that are involved in most RADM processes (Jin 2010). Additionally, ANN's strong learning ability helps to make the system suitable for prediction.

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* (FIS), 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 FL 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), Paek 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 FL to RA. Until recently, Lam et al. (2007) designed a decision model for RA, in which linguistic principles and experiential expert knowledge were transformed into a quantitative-based analysis by using FL. However, their RA 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 earthmoving 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. Nonetheless, so far no work has been done to apply ANN to RA in infrastructure projects.

There are many merging formats of ANN and FL, such as neuro-FISs (where ANN is used as a tool in fuzzy models), fuzzy ANNs (where conventional ANN models are fuzzified), and fuzzy-neural hybrid systems (where fuzzy technologies and ANN are incorporated into hybrid systems) (Lin and Lee 1996). These neurofuzzy techniques have been applied in a variety of construction domains, including a hybrid method combining principal items: ratio estimation and ANFIS for mining of cost estimation data of residential construction projects (Yu and Skibniewski 2010), a fuzzy-neural inference system for decision making in geotechnical engineering (Cheng et al. 2008), a hybrid soft computing system for mining of complex construction databases (Yu 2007), an optimum bid markup calculation methodology in static competitive bidding environments using neurofuzzy systems and multidimensional risk analysis algorithms (Christodoulou 2004), an automated data interpretation system using neurofuzzy approaches for sanitary sewer pipeline condition assessment (Chae and Abraham 2001), a neurofuzzy design system based on a loose coupling model for preliminary design of concrete box girder bridges (Zhao et al. 2001), and a multicriterion decision model for quantitative constructability analysis based on a neurofuzzy knowledge-based system (Yu and Skibniewski 1999), among many others. However, thus far there has been no work being done to apply neurofuzzy techniques to RA in infrastructure projects.

In this paper, the ANFIS, which 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, is adopted for developing a SynFIS. Fundamentally, ANFIS is a graphical network representation of zeroth-order or first-order Sugeno-type FIS endowed with neural learning capabilities (Jang and Sun 1995). The network is comprised of nodes and with specific functions collected in layers (Tsoukalas and Uhrig 1997). Sugeno FIS, also known as 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 (IVs), 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 (*Fuzzy logic toolbox 2 user's guide* 2007).

Development of NFDSS

Decision support systems (DSSs) are developed to assist problem solvers and decision makers. Basically, there are two approaches to developing DSSs, which are operations research (OR) and artificial intelligence (AI). While OR-based DSSs are normally used to solve well-structured decision problems, AI-based DSSs are used to tackle complex problems that traditional techniques cannot solve (Li and Love 1998). The DSS established in this study is an AI-based DSS because the SynFIS is adopted as its model base subsystem, which is presented later in detail. Because ANN and FL are integrated in the SynFIS, the DSS is titled as a NFDSS. The NFDSS is a single-user system, which means that an operating system or application software is usable only by one person at a time.

The NFDSS was constructed using a four-stage system development methodology, which is based on a generic information system development (Moscato 1998). The four stages of the system development process include (1) designing the architecture of the NFDSS; (2) analyzing and designing the NFDSS mainly by defining functionalities of the system components and understanding how they interact with one another, including building the SynFIS, which is the kernel of the NFDSS; (3) building the prototype in order to learn more about the concepts and design; and (4) evaluating the NFDSS by potential users. The outcome of each stage was fed back to previous stages in order to refine the works in previous stages. Details about all the four stages are reported in the following sections.

Designing NFDSS Architecture

Good system architecture is characterized by clear definitions of the functionalities of various components and accurate demonstration of their interaction with one another and thereby provides a road map for the system building process (Nunamaker et al. 1990). The NFDSS is a single-user system with a two-tiered architecture, which is suitable for developing noncritical applications with light transaction loads such as a DSS (Dickman 1995). On the user side, it is a front-end system that works with users to obtain service requests and present results. On the application software side, it is a back-end system that executes a SynFIS analysis and accesses the database for data management. Both sides were developed and operated in the MATLAB environment. The NFDSS consists of three interrelated components, which are (1) database; (2) model base subsystem (ANFIS); and (3) user interface. These three components are the basic elements in DSS (Pearson and Shim 1995). The NFDSS is executed on a PC as it is a single-user system. By using the MATLAB software installed on the PC, whenever a user sends a request to the NFDSS, the code is processed by a program designed in MATLAB. The basic architecture of the NFDSS is illustrated in Fig. 2.

Analyzing and Designing NFDSS

Analysis and design are important parts of the system development process. During this stage, the domain being studied needs to be understood, various alternatives need to be applied, and proposed solutions need to be synthesized and evaluated (Nunamaker et al. 1990). As a result, system components and a development platform can be determined. In this study, the three interrelated components of the NFDSS are (1) database; (2) model base subsystem; and (3) user interface. The functionality of

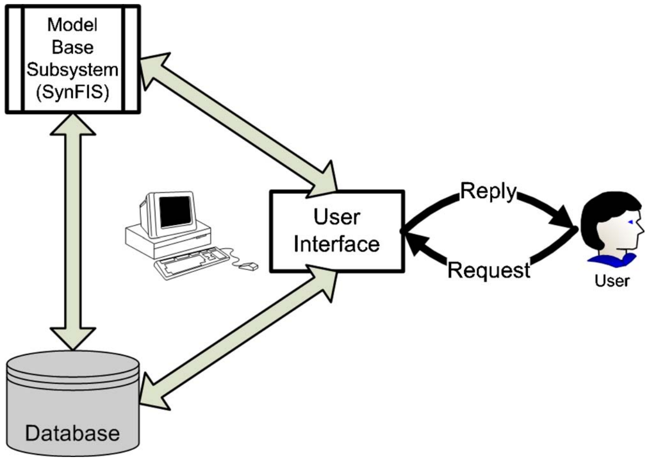

Fig. 2. Components and architecture of NFDSS

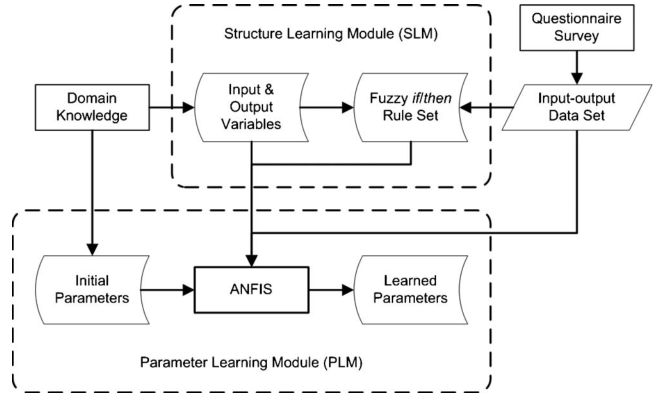

Fig. 3. General structure of SynFIS

the NFDSS is achieved by the interaction and coordination of the three components and the user. The details are discussed in the following sections.

Database

Database is designed for the storage and management of data (Ngai and Wat 2005). In this study, the application software for the database includes MATLAB and Microsoft Excel, which is supported by MATLAB. With MATLAB and Microsoft Excel being used in combination, the database retains (1) the data that were generated in the training process of the SynFIS, including values of all the parameters of the SynFIS set; (2) the data to be obtained from users, including the information about their specified PPP infrastructure projects, which is taken as IVs of the NFDSS; and (3) the data to be generated by the NFDSS, i.e., the forecasted efficient RA strategies.

Model Base Subsystem (SynFIS)

A model base subsystem performs activities to provide analytical capabilities for a DSS (Turban 1995). In this study, a SynFIS was used as the model base subsystem in the NFDSS. When users invoke the process of forecasting an efficient RA strategy regarding a given type of risk in a specified project, an associated program is called to (1) elicit from the users the information that is required for the SynFIS, i.e., the information about their specified PPP infrastructure projects; (2) access required information from the database such as the MFs of IVs and output variable (OV) regarding the set of trained SynFISs; and (3) perform the associated calculation in the SynFIS set for forecasting.

A neurofuzzy system usually involves structure learning and parameter learning. In this study, the SynFIS combines structure and parameter learning into a common framework. To initiate the learning process in the SynFIS, domain knowledge about IVs and OVs 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, which are structure learning module (SLM) and parameter learning module (PLM) (see Fig. 3). By generating fuzzy rules from and adjusting parameters based on the numerical data obtained in the fieldwork, the SynFIS is able to realize the synthetic benefits associated with ANNs and FL.

The tasks in SLM are to determine IVs and OVs 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 SynFIS environment.

The IVs of SynFIS include 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). IV_1 was assessed by a set of three fuzzy values, i.e., "low (L)," "medium (M)," and "high (H)." IV_2–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., "public partner's capability is superior (public)" and "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 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 2010; Jin and Doloi 2008b).

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 (PCA) (see Jin 2010). IV_5 was derived from the respondents' evaluation of the corresponding EU factors in the survey by applying fuzzy operation (see Jin and Doloi 2008a). IV_6 is the RM capability difference between public and private partners and measured by the difference of partner's RM mechanisms. Partner's RM mechanism was derived from the respondents' evaluation of the corresponding observed variables in the survey by using PCA.

Each fuzzy value is a fuzzy set and determined by a MF. The commonly used MFs include Gaussian, triangular, and trapezoidal functions (Lin and Lee 1996). In this study, the Gaussian function was adopted because it is good at achieving smoothness (*Fuzzy logic toolbox 2 user's guide* 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 (see, e.g., Liu and Ling 2005). The 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 1. 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

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Table 1. Fuzzy Values and MFs of IVs

Linguistic variable	Linguistic value	Code	Initial MF parameters (σ, c)	Initial MF $[\mu(x)]$
RM asset specificity (IV_1)	High	H	(0.85, 5)	$\exp[(x-5)^2/(-1.445)]$
	Medium	M	(0.85, 3)	$\exp[(x-3)^2/(-1.445)]$
	Low	L	(0.85, 1)	$\exp[(x-1)^2/(-1.445)]$
Partners' cooperation history (IV_2)	High	H	(1.7, 5)	$\exp[(x-5)^2/(-5.78)]$
	Low	L	(1.7, 1)	$\exp[(x-1)^2/(-5.78)]$
Public partner's RM commitment (IV_3)	High	H	(1.7, 5)	$\exp[(x-5)^2/(-5.78)]$
	Low	L	(1.7, 1)	$\exp[(x-1)^2/(-5.78)]$
Private partner's RM commitment (IV_4)	High	H	(1.7, 5)	$\exp[(x-5)^2/(-5.78)]$
	Low	L	(1.7, 1)	$\exp[(x-1)^2/(-5.78)]$
Environmental uncertainty (IV_5)	High	H	(1.7, 5)	$\exp[(x-5)^2/(-5.78)]$
	Low	L	(1.7, 1)	$\exp[(x-1)^2/(-5.78)]$
Capability superiority (IV_6)	Private partner's capability is superior	Private	(3.4, 4)	$\exp[(x-4)^2/(-23.12)]$
	Public partner's capability is superior	Public	(3.4, −4)	$\exp[(x+4)^2/(-23.12)]$

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 OV of the SynFIS is "RA 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 "fully bearing by public partner," via 3, denoting "equally bearing by public and private partners," to 5, denoting "fully bearing by private partner." As the first-order Sugeno-type FIS was used in SynFIS, 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 section. 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 $\{p_i, q_i, r_i, s_i, t_i, u_i, v_i\}$=consequent parameter set of the ith fuzzy if/then rule. Before being passed 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 while the other parameters were assigned with zero (0) as their initial values. Taking the first case (the Case) of the 44 survey responses with regard to "legislative and political risk (R_L)" as an example, as the target output value in the Case is 4, the consequent parameter set is {0, 0, 0, 0, 0, 0, 4}. The survey and the risks under study are discussed in the section of "Building NFDSS Prototype."

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 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 including (1) determining the membership values of each input value of a given data pair for all fuzzy values of the corresponding fuzzy variable; (2) assigning each input value with a fuzzy value that the input value has the maximum membership value of; and (3) obtaining one rule from each input-output data pair.

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.

In the example case, 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 Step 1 calculation is shown in Column 4 in Table 2. In Table 2, the maximum membership value for each fuzzy variable is highlighted in bold in Column 4. It can be observed that in the Case, the fuzzy values assigned to the input values of $IV_1 - IV_6$ are "high," "low," high, high, low, and "public," respectively. In case 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 that the data set will be expanded to include ambiguous cases.

In the example case, the rule was obtained as below. 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.

Table 2. Determine IF Part of Fuzzy If/Then Rule Based on Input Values of the Case

Fuzzy variable	Numerical value	Fuzzy value	Membership value	Assigned fuzzy value
(1)	(2)	(3)	(4)	(5)
IV_1	1.0	High	**1.000**	High
		Medium	0.063	
		Low	0.000	
IV_2	2.0	High	0.211	Low
		Low	**0.841**	
IV_3	4.0	High	**0.841**	High
		Low	0.211	
IV_4	4.7	High	**0.981**	High
		Low	0.098	
IV_5	3.0	High	0.494	Low
		Low	**0.508**	
IV_6	1.0	Public	**0.675**	Public
		Private	0.341	

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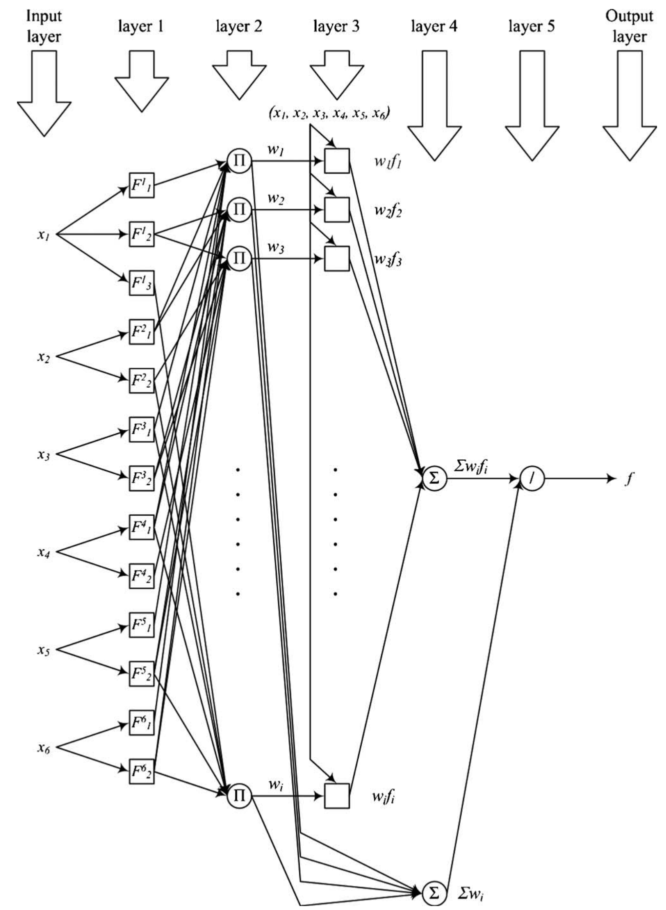

Fig. 4. ANFIS architecture

IF IV_1 is "high," *AND*
IV_2 is "low," *AND*
IV_3 is "high," *AND*
IV_4 is "high," *AND*
IV_5 is "low," *AND*
IV_6 is "public,"
THEN OV is $f_1 = p_1 \times 1.0 + q_1 \times 2.0 + r_1 \times 4.0 + s_1 \times 4.7 + t_1 \times 3.0 + u_1 \times 1.0 + v_1 = 4$

After the IVs and OVs have been determined and the fuzzy rules obtained, the structure of the neurofuzzy learning model can be established. The SynFIS thus enters into the PLM. The PLM was designed to tune MFs by adjusting antecedent and consequent parameters in order 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 proposed ANFIS in the SynFIS is a multilayer neural network-based FIS. It has five hidden layers besides 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, in which hidden layers are usually difficult to interpret and/or modify. The architecture of the proposed ANFIS is illustrated in Fig. 4, where a square was used to represent "adaptive node," whose function depends on its parameter values, and a circle was used to denote "fixed node," which 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 being the (antecedent) parameter set. Therefore, the output of a node in Layer 1 is defined by

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

where σ_j^k and c_j^k=parameters of the MF that represents 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 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 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 being 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 represents the 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

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

The other node calculates the sum of all 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 "/," which 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

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

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 OV is RA strategy.

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) was applied directly to the PLM. The hybrid learning algorithm uses a gradient descent-based BP algorithm and a LSE algorithm to optimize the antecedent and consequent parameters, respectively. In order 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 paper. Please refer to the cited works for complete coverage on the related topics.

User Interface

The design of the user interface is a key element in DSS functionality. The interface of a DSS should provide easy communication between the user and the system (Turban 1995). In this study, a graphic user interface (GUI) that was designed in the MATLAB functions as the user interface component of the NFDSS. Users invoke the NFDSS by launching the MATLAB software and keying in the command line window the m-file name of the GUI, which is MYNFDSS. The GUI component is then loaded into the workspace. The introduction part of the GUI is presented to users first (see Fig. 5). Users are asked to specify for which type of risk they are going to use the NFDSS to forecast efficient RA strategies. The prototype of the NFDSS only provides functions for three risks, as shown in Fig. 5. However, based on user's specific requirement, it is easy to adapt the NFDSS for any particular risk. Then users are requested to specify a PPP infrastructure project and provide information about their specified PPP infrastructure projects that is required for running the SynFIS including the information regarding environmental uncertainty, partner's RM routines, partner's cooperation history, partner's RM commitment, and partner's RM capability (see, e.g., Fig. 6). Finally, after obtaining all required information and data, the results generated by the SynFIS set are presented as suggested efficient RA strategies in the GUI (see Fig. 7).

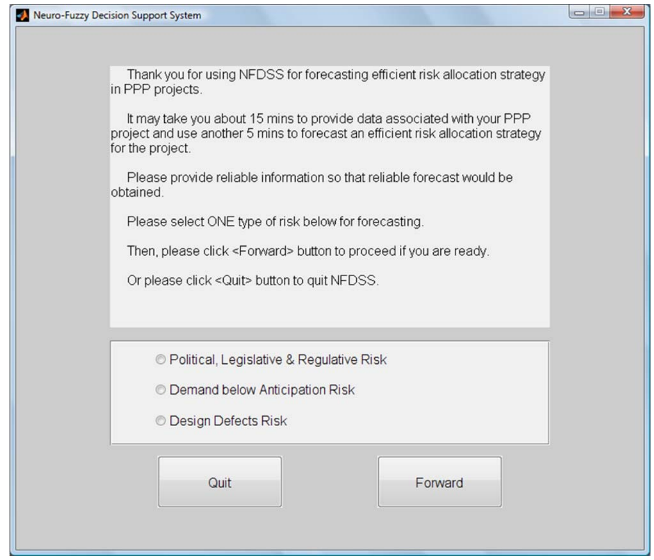

Fig. 5. Introduction of GUI of NFDSS

Building NFDSS Prototype

The implementation of a system demonstrates the feasibility of the design and the utility of the functionalities that are envisaged (Nunamaker et al. 1990). Building a prototype system is a process that allows insight into the problems and the complexity of a system during development research. The NFDSS was built using the MATLAB software packages. The body of the entire NFDSS, including the database, the model base subsystem, and the user interface, was written using the MATLAB programming language. The prototype was run on the Windows XP platform.

The major task is the training of the model base subsystem (SynFIS). The training data set was obtained in an industry-wide questionnaire survey. Based on the theoretical framework, a set of questionnaire was designed for the survey. The questionnaire asked respondents to provide reliable information about a PPP project, in which they had appropriate involvement and/or knowledge. The main information to provide includes the evaluation of

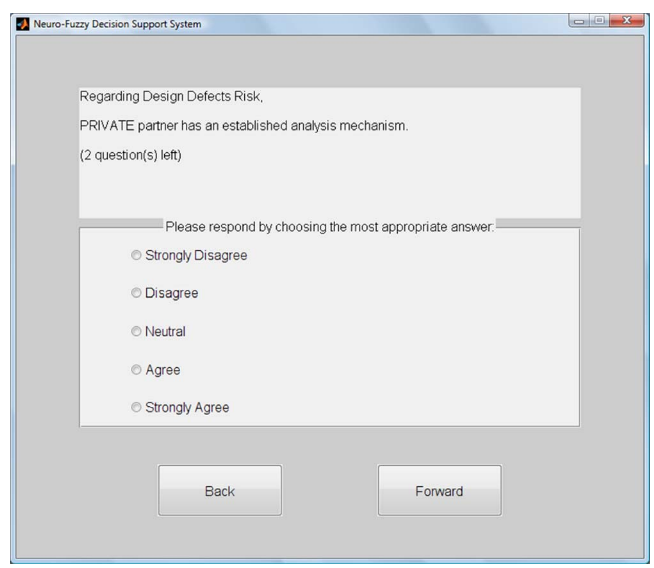

Fig. 6. Data collection of GUI for partner's RM capability

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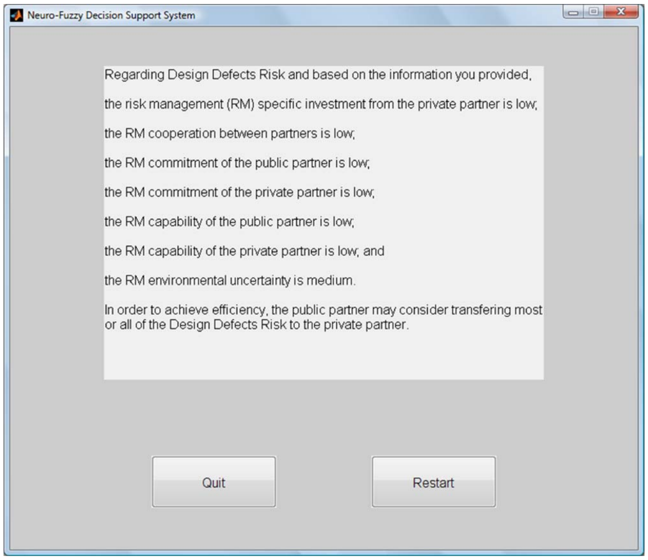

Fig. 7. Results' presentation of GUI of NFDSS

the aforementioned risk management service transaction characteristics, the adopted RA strategies, and the perceived most efficient RA strategies in the specified PPP projects. Respondents were also required to provide information about their PPP experience and designation.

While RA strategies may vary from risk to risk and from project to project, the mechanism of RADM remains the same for different risks (Jin 2010; Jin and Doloi 2008b). Therefore, to follow the triangulation concept in academic research (Hammersley and Atkinson 2007) and facilitate a comparison of evaluation results among the NFDSS established in the current paper, the MLR models in the work of Jin (2010), and the FIS in the work of Jin and Doloi (2009), the results regarding three risks are reported in this paper. The three selected risks are (1) "defects in design" in development stage (coded as R_D); (2) "demand below anticipation" in operation stage (coded as R_O); and (3) "adverse changes in law, policy, or regulations" during the life cycle (coded as R_L). They are selected for report 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, 1995) and (2) they exist in different stages of project life cycle. Similar strategies have been adopted in previous research (see, e.g., Kangari and Riggs 1989).

Following a pilot survey during a PPP workshop and consequent refinement of the questionnaire, an industry-wide 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 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% is acceptable for a survey of this nature (De Vaus 2001). The profile of the respondents is shown in Table 3. They were deemed appropriate to provide reliable response to the survey due to their ample experience

Table 3. Profile of Survey Respondents (Jin 2010)

Item	Category	Frequency	(%)
Respondents' designation	Senior level	41	93.2
	Middle 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

in PPP projects and in the construction industry. The returned questionnaires were checked and edited to ensure completeness and consistency.

The training data 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. In order 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. Early stopping training method has been proved to be 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. The multifold cross-validation method may thus be used (see Haykin 1999, p. 218). An extreme form of multifold cross validation, known as *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 for 44 times. At each time, 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

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

where x_i=SynFIS-forecasted RA strategy in ith case; t_i =suggested efficient RA strategy in ith case; and n=number of cases, which is 44. The training results are presented in Table 4.

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Table 4. Training Results of SynFIS

Risk	$\text{RMSE}_{\text{est}}^{\text{avg}}$	$\text{RMSE}_{\text{val}}^{\text{avg}}$
1	0.0035	0.0098
2	0.0498	0.0433
3	0.0998	0.1893

Evaluating NFDSS

After the prototype of the NFDSS had been developed, it was tested and evaluated. Through system evaluation, information can be captured on whether the system meets the needs of users and to what extent (Ngai and Wat 2005). First, all of the NFDSS components were tested individually for accuracy. The trained SynFIS, which is the model base subsystem, was then integrated into the NFDSS and the system was tested collectively for accuracy and completeness. These tests ensured that the designed functions of the NFDSS could be performed appropriately.

The test data set was obtained from a panel of five experts. The experts were asked to respond to the survey questionnaire and each provides information of a PPP project. The profile of the experts is shown in Table 5. Their responses are deemed reliable. The results based on the test data set when using NFDSS were compared with those using MLR technique (see Jin 2010) and those using FIS models (see Jin and Doloi 2009).

A set of performance indices was used, which included *error* (*e*), *percentage error* (*PE*), *mean percentage error* (*MPE*), *mean absolute percentage error* (*MAPE*), and RMSE. These performance indices have been adopted in many previous research works (e.g., Jang 1993; Soetanto and Proverbs 2004; Liu and Ling 2005; and many others). Except for RMSE, which has been defined previously, the performance indices are defined as follows:

$$e_i = T_i - O_i \tag{9}$$

$$\text{PE}_i = \frac{T_i - O_i}{T_i} \times 100\% \tag{10}$$

$$\text{MPE} = \sum_{i=1}^{n} \text{PE}_i \Big/ n \tag{11}$$

$$\text{MAPE} = \sum_{i=1}^{n} |\text{PE}_i| \Big/ n \tag{12}$$

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

The ratings of the six IVs for each test case regarding three risks were fed into the NFDSS prototype 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 2010). The efficient RA strategies forecasted by the models were compared to those specified by the experts. The evaluation results of NFDSS' accuracy are shown in Tables 6 and 7. For each of the five cases regarding each risk, the lower value of each performance index was highlighted in bold. In Table 6, regarding each risk, the NFDSS generated lower *e* and PE. This indicates that the NFDSS is accurate and consistent in terms of forecast performance.

Furthermore, in Table 7, regarding all three risks under analysis, the upshot is that the performance of the NFDSS in terms of RMSE, MPE, and MAPE is much better than that of the MLR and FIS models. Compared with MLR models, NFDSSs have averagely achieved a significant improvement in RMSE by 87.80%, MPE by 94.15%, and MAPE by 92.45%. Compared with FIS models, NFDSSs have also achieved a considerable improvement in RMSE by 82.43%, MPE by 91.47%, and MAPE by 89.98%. The comparison is demonstrated in Figs. 8(a–c). It is noted that, across the three performance indices, errors of NFDSS regarding R_L are marginally higher than those regarding R_D and R_O. Although it has little effect on NFDSS forecast performance, the probable explanation would be that it is relatively more difficult to accurately forecast efficient allocation strategies for risks lingering throughout the life cycle of a project, such as R_L.

Taking R_L as an example, the NFDSS may generate an error of ± 0.1113 in average, may have the propensity to overforecasting a bit (+2.2728%), and may contain 2.7400% error in the forecast averagely. In comparison, the MLR and FIS models may, respectively, generate errors of ± 0.7428 and ± 0.3649 in average, may have the propensity to underforecasting by -19.7632 and -11.7053%, and may contain 31.9375 and 14.9613% errors in the forecast averagely. That is to say, for instance, when an efficient RA strategy for R_L is supposed to be "equally shared by partners" (or 3 on a five-point Likert scale), the relevant NFDSS generally gives an accurate forecast while the relevant MLR and FIS models may suggest "shared by partners but either public or private partner takes a much higher portion of the risk" (or 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 NFDSS is valid and robust and has captured the essential components of the underlying nonlinear and uncertain dynamics.

The efficacy of a system is usually determined through evaluations by potential users against the criteria of its effectiveness, which is the ability of the system to accomplish its objectives, and its usability, which is the ease of use of the system (Gasching et al. 1983). In this study, an evaluation form was designed based on these criteria. The effectiveness and usability of the NFDSS were measured using five questions on a five-point Likert scale, which include 1 (strongly disagree), 2 (disagree), 3 (undecided/neutral), 4 (agree), and 5 (strongly agree). Consequently, the ability of the system to accomplish its objectives and the ease of use of the system were reflected. The evaluation results of the NFDSS' efficacy were used as the other indicator of the success or failure of the NFDSS.

The efficacy of NFDSS was evaluated by the experts who were invited to provide data for testing the accuracy of the

Table 5. Profile of Experts (Jin and Doloi 2009)

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

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Table 6. Comparison of Evaluation Results among NFDSS, MLR, and FIS Models (*e* and PE)

		NFDSS		MLR		FIS	
Risk	Case	*e*	PE (%)	*e*	PE (%)	*e*	PE (%)
R_D	1	**−0.0047**	**−0.2325**	−0.1441	−7.2049	0.5000	25.0000
	2	**0.0004**	**0.0184**	0.5672	28.3600	0.5008	25.0400
	3	**−0.0004**	**−0.0352**	−0.9440	−94.4000	−0.4942	−49.4200
	4	0.1467	4.8887	−0.2700	−9.0006	**0.0000**	**0.0000**
	5	**−0.0314**	**−3.1359**	0.2265	22.6505	−0.5000	−50.0000
R_O	1	**0.0063**	**0.3138**	−0.4404	−22.0182	0.5280	26.4000
	2	0.0226	0.7548	0.2170	7.2333	**0.0000**	**0.0000**
	3	**0.0234**	**2.3397**	−0.1414	−14.1415	−0.4212	−42.1200
	4	**−0.0094**	**−0.9443**	−0.6025	−60.2533	−0.4998	−49.9800
	5	**−0.0607**	**−6.0724**	−0.1292	−12.9197	−0.5000	−50.0000
R_L	1	**0.2065**	**4.1300**	1.1284	22.5690	0.4070	8.1400
	2	0.0322	1.0718	0.2360	7.8667	**0.0000**	**0.0000**
	3	**−0.0350**	**−1.1680**	−0.1156	−3.8517	−0.5000	−16.6667
	4	**0.0310**	**3.0958**	−1.1400	−114.0000	−0.5000	−50.0000
	5	0.1270	4.2342	−0.3420	−11.4000	**0.0000**	**0.0000**

NFDSS. They were deemed as potential users because they were among the RA decision makers in their PPP infrastructure projects. The NFDSS was demonstrated to the five experts and they were asked to evaluate the NFDSS by answering the questions in the evaluation form. Their responses are summarized in Table 8. Most potential users strongly agreed that the NFDSS is easy to understand and use (with a mean score of 4.8) and easy to interact with (with a mean score of 4.6). They also agreed that the NFDSS is an effective decision support tool (with a mean score of 4.0) and can provide reliable (with a mean score of 4.2) and practical results (with a mean score of 4.4). Based on the results of the evaluation, the NFDSS prototype was seen as a promising system for selecting efficient RA strategies for PPP infrastructure projects.

Table 7. Comparison of Evaluation Results among NFDSS, MLR, and FIS Models (RMSE, MPE, and MAPE)

Performance index	Model	R_D	R_O	R_L
RMSE	NFDSS	**0.0671**	**0.0312**	**0.1113**
	MLR	0.5211	0.3580	0.7428
	Improvement (%)	*87.12*	*91.28*	*85.01*
	FIS	0.4461	0.4373	0.3649
	Improvement (%)	*84.95*	*92.86*	*69.48*
MPE (%)	NFDSS	**0.3007**	**−0.7217**	**2.2728**
	MLR	−11.9190	−20.4199	−19.7632
	Improvement (%)	*97.48*	*96.47*	*88.50*
	FIS	−9.8760	−23.1400	−11.7053
	Improvement (%)	*96.96*	*96.88*	*80.58*
MAPE (%)	NFDSS	**1.6621**	**2.0850**	**2.7400**
	MLR	32.3232	23.3132	31.9375
	Improvement (%)	*94.86*	*91.06*	*91.42*
	FIS	29.8920	33.7000	14.9613
	Improvement (%)	*94.44*	*93.81*	*81.69*

Application of NFDSS to a Real PPP Infrastructure Project

The established NFDSS is applied to the process of forecasting efficient RA strategy for "demand risk" (R_O) of the EastLink PPP project (the project) in Melbourne, Australia. The project, with a construction cost of AU$2.5 billion, is the largest road project ever constructed under the Victorian Government's *Partnerships Victoria* policy (VIC DOI 2004). The 39-km-long motorway provides a vital connection for the 1.5-million people living in Melbourne's eastern and southeastern suburbs and the key industrial areas along the project corridor (SEITA 2007).

The private consortium (ConnectEast Pty Limited, Victoria, Australia) financed, designed, and constructed the EastLink free-

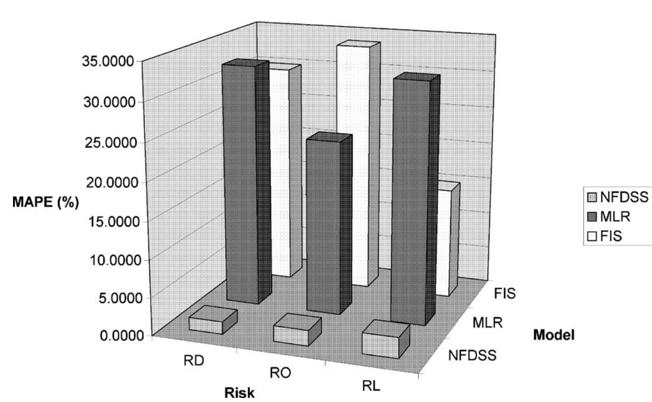

Fig. 8. Comparison of evaluation results among NFDSS, MLR, and FIS models

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Table 8. Results of Evaluation of NFDSS Prototype by Potential Users

Number	Statement	Median	Mean
1	The system is easy to understand and use	5	4.8
2	The system is easy to interact with	5	4.6
3	The system provides an effective means to determine optimal RA strategies for PPP infrastructure projects	4	4.0
4	The system generates reliable information about optimal RA strategies in PPP infrastructure projects	4	4.2
5	The system generates practical information about optimal RA strategies in PPP infrastructure projects	4	4.4

way including the provision of the tolling system. The private sector will also provide operation, maintenance, repair, security, and other customer services for the freeway for a period of 35 years (SEITA 2007). At the end of the concession period, the freeway and its plant and equipment will be handed over to the Victorian Government (VIC DOI 2004). In return, the government allows the private sector to toll the road during the operational phase of the project. However, the government required the private sector to entirely assume the demand risk. That is, debt repayments to the financiers from the contractor are based on usage payments only.

After relevant data had been collected, the NFDSS proceeded by running the embedded programs. The IVs and OVs of the NFDSS are presented on the results' GUI, as shown in Fig. 9. These variables are presented in linguistic values rather than numeric values so that the imprecision and uncertainty intrinsic in language can be addressed. It can be seen that the private partner's capability to tackle the demand risk is low while the public partner's capability is high. General environment for managing the risk is highly uncertain although both sectors are holding high commitment to managing the risk. Under such circumstances, transferring demand risk to the contractor would result in a higher price to manage the risk and even create additional significant risks for both parties (NAO 1999). The efficient RA strategy forecasted by the NFDSS thus suggests that government bears most or all of demand risk, which does not match the strategy that was adopted in the project (X.-H. Jin, "A framework for efficient RA

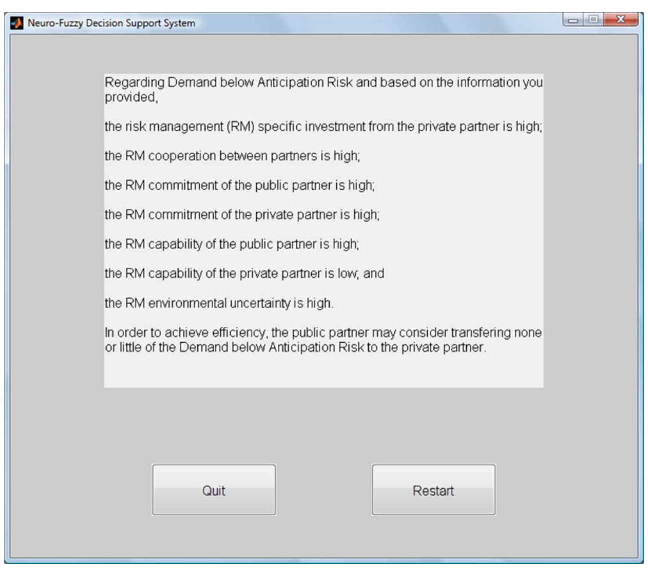

Fig. 9. Application of NFDSS to the EastLink PPP project: results' presentation of GUI regarding demand risk (R_O)

in public-private partnership projects using neuro-fuzzy techniques," unpublished Ph.D. thesis, The University of Melbourne, Melbourne, Australia, 2009). Since the project had not formally entered into the operation stage when this study was completed, whether or not the adopted strategy is efficient could not be verified. However, a review of traffic by ConnectEast in 2009 revealed a major shortfall between observed volumes and revenues and projections made in 2004, with a maximum shortfall in average daily volumes only being 40% of the projections made in 2004 (Chappell 2009b). As a result, ConnectEast has booked a net loss of AU$531.58 million for the year ended June 30, 2009 and written down the value of its EastLink toll road concession by AU$400 million to about AU$2.9 billion (Chappell 2009a). The impact on the users is that the average trip toll was further up 5.2% on November 2009 (The Age 2009). It is now obvious that the value for money expected from transferring demand risk to the private partner has not been achieved in the EastLink PPP project.

Conclusion

RA plays a critical role in PPP infrastructure projects. Project success (or failure) is contingent on whether the adopted RA strategy can lead to efficient risk management (or not). Previous research has tried to model RADM process by using traditional probability-based approaches such as MLR technique. However, the resultant models cannot be used to accurately forecast efficient RA strategies due to the inherent limitations in probability-based analysis, such as not considering nonlinear relationship and failing to identify all the factors necessary to reflect realistic situations. In this paper, the neurofuzzy approach was innovatively and successfully applied to establishing a NFDSS for facilitating efficient RA in PPP infrastructure projects, which had not been attempted in any previous research. Neurofuzzy approach was chosen because it combines the strengths of ANNs and FISs and thus possesses strong learning ability and the capability to handle unspecificity, uncertainty, nonlinearity, and complexity.

In this study, an established theoretical framework drawing on the TCE and the RBV of organizational capabilities was adopted as the architecture of the kernel component of the NFDSS. The NFDSS comprises three interrelated components, namely, (1) database; (2) model base subsystem; and (3) user interface. The four-stage development process of the NFDSS includes (1) designing the architecture of the NFDSS; (2) defining and designing the functionalities of the system components and their interaction; (3) building the prototype of the NFDSS; and (4) evaluating the NFDSS by potential users.

The core component of the NFDSS is a SynFIS. ANNs and FISs were integrated into each other to build the SynFIS, which

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serves as the model base subsystem of the NFDSS. The learning process of the SynFIS was implemented in two sequential learning modules, which are SLM and PLM. The prototype SynFIS was established through an innovative training process based on the data obtained in a questionnaire survey. The prototype of the NFDSS was evaluated by a comparison with MLR and FIS models. The evaluation results indicated that the NFDSS performs much more efficiently and reliably in terms of accuracy and efficacy.

The results have further confirmed that when making decisions on RA strategies for PPP projects, decision makers should carefully analyze and evaluate partners' RM routines, commitment, capability, and cooperation history. Various environment uncertainty factors should also be taken on board. Although these variables usually bear their inherent features of unspecificity, uncertainty, nonlinearity, and complexity, with the established NFDSS, RADM process in PPP infrastructure projects now can be successfully modeled and efficient RA strategies now can be accurately forecasted. This neurofuzzy model, with its user-friendly GUIs, is expected to help industrial professionals to select optimal RA strategies to achieve efficient risk management and the ultimate project success when adopting PPP procurement models.

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