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Modelling optimal risk allocation in PPP projects using artificial neural networks

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Abstract

This paper aims to establish, train, validate, and test artificial neural network (ANN) models for modelling risk allocation decision-making process in public–private partnership (PPP) projects, mainly drawing upon transaction cost economics. An industry-wide questionnaire survey was conducted to examine the risk allocation practice in PPP projects and collect the data for training the ANN models. The training and evaluation results, when compared with those of using traditional MLR modelling technique, show that the ANN models are satisfactory for modelling risk allocation decision-making process. The empirical evidence further verifies that it is appropriate to utilize transaction cost economics to interpret risk allocation decision-making process. It is recommended that, in addition to partners' risk management mechanism maturity level, decision-makers, both from public and private sectors, should also seriously consider influential factors including partner's risk management routines, partners' cooperation history, partners' risk management commitment, and risk management environmental uncertainty. All these factors influence the formation of optimal risk allocation strategies, either by their individual or interacting effects.

Keywords: Risk allocation; Transaction cost economics; Artificial neural networks; PPP/PFI; Australia

1. Introduction

Public–Private Partnership (PPP) arrangements are rapidly becoming the preferred way to provide public services in many countries. Risk allocation in PPP projects is fundamentally different from that in traditional public projects, where the public sector purchases an asset from private sector contractors and consultants whose liability is limited to the design and construction of the asset and financial and operational risks remain with the public sector. In PPP projects, the government bears little or no asset-based risk and is entitled to reducing payments, abatements and compensation if the service is not delivered to the specified standards. Accordingly, one of the most important drivers for value-for-money is risk transfer, which means appropriate risks can be transferred to the private sector, who is supposed to be capable of managing those risks better (Hayford, 2006). As a result, cheaper and higher-quality infrastructure services may be provided than in conventional way.

Unfortunately, risk transfer is often handled poorly in PPP projects (Ng and Loosemore, 2007). A common perception that privatization involves transfer of all risks to the private sector is prevalent in many countries. 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. Furthermore, the complex arrangements and incomplete contracting in PPP projects have led to increased risk exposure for both public and private partners (Jin, 2010; Jin and Doloi, 2008b). Effective risk allocation in PPP projects is therefore challenging and demanding.

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In this paper, the determinants of efficient risk allocation were identified based on the transaction cost economics (TCE) theory and the resource-based view (RBV) of organizational capabilities. Accordingly, a theoretical framework was proposed to model the risk allocation decision-making process in PPP projects. In the next section, the risk allocation decision-making determinants and theoretical framework are presented. Then, the artificial intelligence technique based on artificial neural networks (ANNs) is briefly reviewed. Research methodology including an industry-wide survey in Australia is then reported, followed by a detailed description of the construction, training, and evaluation of ANN models. Finally, a brief conclusion is presented.

2. Determinants of risk allocation strategy

Risk allocation practices in PPP projects have been found highly variable, intuitive, subjective and unsophisticated (Ng and Loosemore, 2007). Given its critical importance in PPP projects, a number of studies have been conducted to explore how to achieve efficient risk allocation, such as Arndt (1999) developing a framework for efficient risk allocation to help obtain the optimum outcomes from the BOOT delivery method, Thomas et al. (2003) conducting a risk perception analysis in the Indian BOT roads sector to evaluate the risk criticality, risk management capability, risk allocation/sharing preference, and factors influencing risk acceptance of major stakeholders, Faulkner (2004) proposing that sharing risks rather than transferring them and a win–win mutual gain be the characteristics of true PPPs, Hayford (2006) proposing that optimal risk allocation should have sufficient flexibility to enable the partners to deal with external changes and events, Medda (2007) exploring the behaviour of the public and private partners when confronted with opposite objectives in the allocation of risks, and Ng and Loosemore (2007) analysing the rationale behind decisions about risk distributions between public and private sectors and their consequences and demonstrating the complexity and obscurity of risks facing such projects and the difficulties in distributing them appropriately. However, these studies either deems the risk allocation process as one that is only affected by agents' risk attitudes (e.g. Thomas et al. (2003)) or management capabilities (e.g. Arndt (1999)); or lacks theoretical foundations and/or empirical evidence to support their submissions.

More importantly, the design of risk allocation has rarely been judged on a cost–benefit basis (Miller and Lessard, 2001) given the claim that appropriate risk allocation would significantly reduce transaction cost (Zaghloul and Hartman, 2003). This is probably because research in project management, including risk management, has been concerned mainly with process and technique (Walker and Chau, 1999; Winch, 2006). While both aspects aim at increasing efficacy, neither is successful in understanding which kind of existing governance structures best suits a particular construction project in terms of efficiency and why (Jin, 2010). Miller and Lessard (2001) argued that costs of controlling risks must fit with expected benefits when dealing with risks in large engineering projects and proposed to adopt a real-options approach. Nonetheless, no further empirical study has been conducted to support their submissions.

Recently, Jin and colleague argue that the transaction cost economics (TCE), if integrated with the resource-based view (RBV) of organizational capability, can contribute to this and allow a more logical and holistic understanding and interpretation of the risk allocation decision-making process (Jin, 2010; Jin and Doloi, 2008b). The rationale and relevant framework are briefly discussed below.

Transaction costs are the costs of running the economic system (Arrow, 1969). Accordingly, TCE poses the problem of economic organization as a problem of contracting and maintains that there are rational economic reasons for organizing some transactions one way and other transactions another (Williamson, 1985). The principal dimensions with respect to which transactions differ are (1) asset specificity, (2) uncertainty, and (3) frequency (see Williamson (1985, 1996) for details). The consequent organizational imperative is to 'organize transactions so as to economize on bounded rationality while simultaneously safeguarding them against the hazards of opportunism' (Williamson, 1985).

Regarding risk allocation, if a risk is improperly allocated, possible resultant transaction costs may include, among others, (1) the extra costs for clients of a higher contingency (or premium) included in the bid price from contractors; (2) the extra costs for clients of more resources for monitoring the risk management work; (3) the extra costs for clients and/or contractors of recovering lower quality work (i.e. the materialized or deteriorated risk) for a given price; (4) the extra costs for contractors of increasing safeguards (both *ex ante* and *ex post*) against any opportunistic exploitation of one's own risk management service-specific assets by other parties; (5) the extra costs for contractors of the resources dedicated to lodging claims related to the misallocated risk; (6) the extra costs for both parties of dealing with the disputes or litigation related to the misallocated risk (Jin, 2010).

Choosing a risk allocation strategy could actually be viewed as the process of deciding the proportion of risk management responsibility between internal and external organizations based on a series of characteristics of risk management service transaction in question (Jin, 2010; Jin and Doloi, 2008b). Risk allocation in PPP projects is thus 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). However, it has been found that decisions regarding governance structures are strongly influenced by both exchange conditions at the transaction level and organizational capabilities at the firm level (Jacobides and Winter, 2005; Leiblein and Miller, 2003). Unfortunately, the TCE approach has historically neglected the differences in organizational productive capabilities by holding the constraint that firms maintain homogeneous capability (Jacobides and Hitt, 2005).

Non-imitable and non-substitutable organizational capabilities are a key source of inter-firm performance differences (Barney, 1991; Dosi et al., 2000; Nelson, 1991; Rumelt, 1984; Wernerfelt, 1984). Given a specified output level, a less capable organization would incur more costs to improve its capabilities and to meet the requirements (Helfat and Peteraf, 2003). It has been increasingly recognized that the resource-based view of organizational capability explains competitive heterogeneity based on the premise that close competitors differ in their capabilities in important and durable ways (Helfat and Peteraf, 2003). Therefore, a more complete understanding of the organization of economic activity requires a greater sensitivity to the interdependence of production and exchange relations (Madhok, 2002). In PPP projects, partners' organizational capabilities in risk management are currently deemed as a major determinant of who should be responsible for various risks. It is believed that by relaxing its constraint that firms maintain homogeneous capability and by being integrated with the RBV, the traditional TCE will provide a more logical and holistic understanding of governance decision.

According to Jin (2010), following TCE and RBV, the determinants of risk allocation decision-making, i.e. the characteristics of a risk management service transaction, can be categorized into:

(1) Private partner's risk management routines (IV_1). IV_1 embodies competence in carrying out risk management activities and indicates that alternative uses could have been achieved without sacrificing productive value. It reversely approximates to asset specificity of TCE. This is because the principal factor in explaining TCE is asset specificity, which increases the transaction costs of all forms of governance (Williamson, 1996, p.106).
(2) Partners' cooperation history (IV_2). IV_2 approximates to transaction frequency of TCE. One of the most important factors in partnership success is previous partnership experience (Jin and Ling, 2005). Unlike existing goods, efficient risk management in building and construction projects cannot be obtained by a one-off transaction and requires time to develop (Monteverde and Teece, 1982). Because the cost of managing relationship is also a type of governance cost, transaction frequency must also be considered in any risk management service transactions (Jin, 2010).
(3) Partners' risk management commitment, including public partner's risk management commitment (IV_3) and private partner's risk management commitment (IV_4). IV_3 and IV_4 reversely match behavioural uncertainty of TCE. Generally, an organization can better manage the challenges of communication and governance that occur over the risk management process internally than with an external supplier. The communication and governance advantages of working internally become increasingly apparent as uncertainty increases (Helper, 1991; Williamson, 1985: 140–153). Beyond a certain high level of uncertainty, internal risk management may offer the lowest total cost. Consequently, uncertainty is another critical factor to be considered when deciding risk allocation strategies. Because TCE practically recognizes behavioural uncertainty in addition to primary and secondary uncertainties (Williamson, 1985), uncertainty in a risk management service transaction is categorized into two distinct but related groups, i.e. project environmental uncertainty and partner's behavioural uncertainty.
(4) Risk management environmental uncertainty (IV_5). IV_5 matches environmental uncertainty of TCE. This is because, as previously mentioned, TCE practically differentiates primary and secondary uncertainties from behavioural uncertainty (Williamson, 1985).
(5) The superiority of private partner's risk management mechanism to public partner's (IV_6). IV_6 approximates the organizational capability difference in RBV. As aforementioned, constraints on the production costs of goods and services to be transacted, such as 'mature' and in a 'steady state', need to be relieved because of the heterogeneity of organizational capabilities (Jin, 2010). Accordingly, organizational capability, which production costs are greatly contingent on, should be considered.

With the five determinants, a theoretical framework for risk allocation decision-making was established (Jin, 2010) and shown in Fig. 1. According to TCE, by their individual and interacting effects, the five main characteristics represented by the six independent variables (*IV*s) will serve to predict a cost-efficient risk allocation strategy (i.e. the dependant variable (*DV*)), which is the efficient governance structure in the view of TCE (Jin, 2010). That is, in a risk management service transaction, the proportion of a given type of risk transferred to a private partner depends on the level of the six *IV*s. This proportion or strategy can be 100% (entirely transfer or 'buy'), 0% (entirely retain or 'make'), or somewhere in-between ('make and buy'), e.g. 50% (equally bear). With the TCE assumption, the inherent mechanisms assign different risk

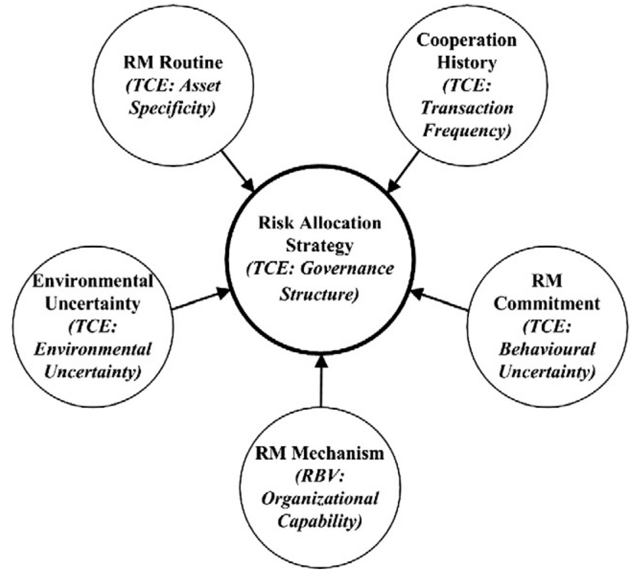

Fig. 1. Theoretical framework for risk allocation decision-making in PPP projects.

management service transactions to different governance structures (risk transfer proportions) in order to economize transaction cost.

The constructs of the theoretical framework have been further operationalized (see Table 1). For the sake of brevity, the operationalization is briefly discussed here. The *asset specificity* of a risk management service transaction in the theoretical framework was operationalized as the risk management routine of a private partner. The level of a private partner's risk management routine was reversely measured by their experience level of managing a particular risk in similar projects on a five-point Likert scale. The rationale is that the higher the experience level, the more alternative uses the risk management capability had been deployed for, and accordingly, the lower specificity the risk management capability possesses.

Transaction frequency is operationalized as partners' cooperation history in similar projects, the level of which is measured by the number of similar projects in which the partners have cooperated. The implicit assumption behind the link between partnership experience and risk management success is that there are learning effects that enable organizations to develop a 'relational capability' (Dyer and Singh, 1998; Kale et al., 2002).

Partners' *behavioural uncertainty* is reversely operationalized as partners' commitment to managing a given type risk. This is because opportunistic behaviour and commitment are closely related in a reserved way (Jin, 2010). The organizational risk management commitment is measured by the aggregate level of three indicators on a five-point Likert scale, viz. a partner's willingness to put in greater effort than normal to manage a risk (Ward et al., 1991); a partner's confidence in managing risk (Barnes, 1983); and a partner's expectation on possible gains by managing risk (Abrahamson, 1973).

The *project environmental uncertainty* in the theoretical framework was operationalized as the uncertainty of risk factors. This is because the evaluation of project environmental uncertainty can be made through risk analysis (Han and Diekmann, 2004) and risk factors better describe the risk-related situations that can be individually assessed with a limited quantity of vague information (Tah and Carr, 2000). Based on the literature, risk factors were categorized in this study into four groups, i.e. institutional; social and industrial; economic; and project-specific factors. In order to describe risk factors using a common language, they were coded in a hierarchical risk breakdown structure. The classification of risk factors is shown in Table 2, together with their codes,

Table 1
Operationalization of theoretical framework constructs.

Construct	Variable	Code	Description	Measurement
Asset specificity (TCE)	RM routine	IV_1	Private partner's experience in managing risk X	1 = low; 5 = high
Transaction frequency (TCE)	Partner's cooperation history	IV_2	Cooperation history between public partner and leading members of private partner	1 = low; 5 = high
Behavioural uncertainty (TCE)	Public partner's RM commitment	IV_3	Public partner's willingness to put in greater effort than normal to manage risk X; public partner's confidence in managing risk X; public partner's expectation on possible gains by managing risk X (the three variables were subject to a confirmatory factor analysis and statistically converged to one factor)	1 = low; 5 = high
	Private partner's RM commitment	IV_4	Private partner's willingness to put in greater effort than normal to manage risk X; private partner's confidence in managing risk X; private partner's expectation on possible gains by managing risk X (the three variables were subject to a confirmatory factor analysis and statistically converged to one factor)	1 = low; 5 = high
Environmental uncertainty (TCE)	Environmental uncertainty	IV_5	An index obtained from 21 environmental factors using the weighted average method (see Jin and Doloi (2008a))	1 = low; 5 = high
Organizational capability (RBV)	Capability superiority	IV_6	$= IV_6(2)–IV_6(1)$;	
	Public partner's RM mechanism	$IV_6(1)$	Maturity of public partner's identification, analysis, response planning, and monitoring and control mechanisms for risk X (the four variables were subject to a confirmatory factor analysis and statistically converged to one factor)	1 = Immature; 5 = Mature
	Private partner's RM mechanism	$IV_6(2)$	Maturity of private partner's identification, analysis, response planning, and monitoring and control mechanisms for risk X (the four variables were subject to a confirmatory factor analysis and statistically converged to one factor)	1 = Immature; 5 = Mature
Governance structure (TCE)	Risk allocation strategy	DV	Proportion of risk management task transferred from public to private partner for risk X	1 = retain (almost) all; 3 = equally share; 5 = transfer (almost) all

Table 2
Operationalization of environmental uncertainty factors.

Category	Code	EU factor	Description	Measurement
Institutional	EI01	Political system instability	Government policies on infrastructure PPPs are consistent and stable *	1 = Stable 5 = Volatile
	EI02	Legislative system instability	Laws and regulations associated with infrastructure PPPs are incomplete and liable to change	1 = Stable 5 = Volatile
	EI03	Government approval process complexity	Government inclines to follow complex procedures and inflexible rules	1 = Simple 5 = Complex
Social and industrial	ES01	Community resistance	Associated community endorses developing this project *	1 = Supportive 5 = Resistant
	ES02	Related industry instability	Structure of related industry is subject to abrupt changes	1 = Stable 5 = Volatile
	ES03	Supporting infrastructure unavailability	Sufficient supporting infrastructures are available for this project *	1 = Available 5 = Unavailable
Economic	EE01	Regional economy instability	Regional economy is subject to abrupt changes	1 = Stable 5 = Volatile
	EE02	Financial market unreliability	Reliable financing instruments are available in the market *	1 = Reliable 5 = Unreliable
	EE03	Insurance market unreliability	Reliable financing instruments are available in the market *	1 = Reliable 5 = Unreliable
Project	EP01	Project idiosyncrasy	Many similar projects have been delivered in the market *	1 = Identical 5 = Distinct
	EP02	Ambiguity of performance requirement	Facility performance requirements are clearly provided *	1 = Clear 5 = Ambiguous
	EP03	Design complexity	Design of project is complex	1 = Simple; 5 = Complex
	EP04	Construction complexity	Construction of project is complex	1 = Simple; 5 = Complex
	EP05	Operation and maintenance complexity	Operation and/or maintenance of project is complex	1 = Simple; 5 = Complex
	EP06	Unreliability of reference data	All reference data are reliable and accurate *	1 = Reliable 5 = Unreliable
	EP07	Competition in project tendering	Number of private consortia that have been short-listed for contract negotiation	1 = None (0); 2 = One (1); 3 = Two (2); 4 = Three (3); 5 = Four (4) or More
	EP08	Rigidity of contract provision	Contract provision is flexible and accommodates future amendments *	1 = Flexible 5 = Rigid
	EP09	Ineffectiveness of partners communication	Communication between public and private partners is NOT effective	1 = Effective 5 = Ineffective
	EP10	Ineffectiveness of dispute resolution mechanism	Partners have established efficient mechanism for dispute resolution *	1 = Effective 5 = Ineffective
	EP11	Gigantic project scale	The approximate value of project (AU$ million)	1 = value $\leq$ 100 2 = 100 < value $\leq$ 250 3 = 250 < value $\leq$ 500 4 = 500 < value $\leq$ 1000 5 = value > 1000
	EP12	Long concession period	The concession duration of project (years)	1 = duration $\leq$ 5 2 = 5 < duration $\leq$ 10 3 = 10 < duration $\leq$ 20 4 = 20 < duration $\leq$ 30 5 = duration > 30

description, and measurement. These factors are measured by their particular features on a five-point Likert scale, such as system instability and process complexity. A single index is further obtained from these factors to measure project environmental uncertainty using a weighted average method (see Jin and Doloi (2008a)).

The partners' *organizational risk management capability* in the theoretical framework is operationalized as the risk management mechanism of a partner and is measured by its maturity level on a five-point Likert scale. Based on the *PMBOK*, risk management involves the processes of risk identification; analysis; response planning; and monitoring and control (PMI, 2004). These individual processes together determine the soundness of the whole system. Therefore, the aggregated maturity level of all processes is used to measure the maturity level of a partner's risk management mechanism. The difference between public and private partners' risk management capability has an impact on the selection of risk allocation strategy and is thus included in the model as an input.

The *governance structures of a risk management service transaction* are operationalized as different RA strategies, which are measured by the proportion of a given risk to be transferred from public partner to private partner on a five-point Likert scale, where 1, 3, and 5 denote 'retain (almost) all', 'equally share', and 'transfer (almost) all', respectively. According to TCE, the governance structures include hierarchy (internal or 'make'), market (external or 'buy'), and hybrid mode (both 'make' and 'buy') (Williamson, 1996). Correspondingly, in a given situation of the aforementioned features in a PPP project, a specific RA strategy, i.e. a specific proportion of a given risk to be transferred from the public partner to the private partner, will be agreed by partners in order to economize transaction cost. This proportion or strategy can be 100% (entirely transfer or 'buy'), 0% (entirely retain or 'make'), or somewhere in-between ('make and buy'), e.g. 50% (equally bear).

The framework has been tested and generally supported by using multiple linear regression (MLR) technique (Jin, 2010). However, MLR analysis bears a number of inherent limitations, which 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, non-probability-based analysis techniques are required and nonlinear relationships need to be considered for accurately modelling risk allocation decision-making process (Jin and Doloi, 2008b). One suitable approach is using *artificial neural networks* (ANNs), which possess the capability to handle nonlinearity and complexity that are involved in most risk allocation decision-making processes (Jin, 2010). Additionally, ANN's strong learning ability helps to make the system suitable for prediction. Therefore, the discovery and validation of the mechanisms of risk allocation decision-making processes by using ANN techniques adds significant value to this study.

3. Research methodology

While it is admitted that risk allocation strategies may vary from risk to risk and from project to project, the mechanism of risk allocation decision-making remains the same for different risks in the TCE view of governance decision. Therefore, to follow the principle of parsimony in academic research, the risk of 'demand below anticipation' in operation stage (coded as RO) is selected as an example. This risk is not only the major but the most controversial risk in PPP projects (Tiong, 1990). It has been deemed as one of the major challenges that PPPs face (Carrillo et al., 2006; Jin and Doloi, 2008b; Tiong, 1990, 1995). Demand forecasts were found to vary widely from reality often by 20–30% and thus accurate demand forecasts are extremely difficult (Medda, 2007; Ng and Loosemore, 2007). Such overestimation often leads to project underperformance or even failure because infrastructures are usually inflexible to adapt to unforeseen demand scenarios due to their large scale, indivisibility and immobility (Miller and Lessard, 2001). The Cross City Tunnel project in Sydney, Australia is a recent example of disastrous impact of such risks. Its patronage was barely a third of the 90,000 daily trips forecast (Salusinszky, 2006). The project went into receivership in December 2006 because it was unable to service AU$580 million in debts (Dasey, 2007).

In order to evaluate the theoretical frameworks (see Fig. 1), different models using ANNs were developed accordingly. Based on the operationalized constructs, a set of questionnaire was designed for an industry-wide survey (see Appendix 1). 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 the aforementioned risk management service transaction characteristics, the adopted risk allocation strategies, and the perceived most efficient risk allocation strategies in the PPP projects specified by the respondents. Respondents were also required to provide information about their PPP experience and designation.

A pilot survey was first conducted during a university-funded PPP workshop. Among 65 invited attendants from industry who have proper knowledge and experience in PPP projects, six provided feedbacks on the relevance, accuracy, phrasing, sequencing and layout of the questionnaire. Following the pilot survey and consequent refinement of the questionnaire, an industry-wide questionnaire survey was carried out in Australia, which constituted the primary data collection method in this study. The target population of the survey was all the professionals and decision-makers who have been involved in risk management of PPP projects in Australia. They include people from both public and private sectors. However, random sampling is difficult due to the difficulty in finding out the exact population. Therefore, judgmental sampling was used, in which a sample is drawn using judgmental selection procedures (Tan, 2004). Due to the highly technical and specialized nature of the survey, the key informant approach was used for selecting potential respondents in the survey. The key informant approach is appropriate when the respondents who, by virtue of their organizational positions, can provide opinions and perceptions that can validly reflect those of other key decision-makers in their organization can be identified (Li and Atuahene-Gima, 2002; Parmigiani, 2007; Phillips, 1981). In this study, these knowledgeable respondents were identified by firstly identifying PPP infrastructure projects in Australian market, then identifying major partners of the identified projects, and finally identifying professionals and decision-makers in major partners' organizations.

In total, 386 questionnaires were distributed. In order to increase the response rate, it was promised to offer a summary of the survey results to the respondents and reminders were sent to potential respondents one week before the initial deadline. One-month extension was granted to allow for response delays due to various reasons. Within three months' time, 44 useful responses were received. The survey response rate of 11.4% is not high but acceptable for social science research of this nature and scale (De Vaus, 2001). This low response rate may be due to the facts that PPP is such a sensitive topic currently within the industry that some potential respondents refused to respond to the questionnaire just in fear that they may disclose information about past or current PPP projects that they had

Table 3
Profile of survey respondents.

Item	Category	Freq.	%
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

been involved in although they were guaranteed with anonymity. One official from a state government, for instance, refused to participate in the survey because he was concerned about 'the confidential nature of the financial information' that may be disclosed.

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 in PPP projects and in the construction industry. A survey of this nature might have suffered from the possibility of bias and the possibility that the respondents would not really think through some of the questions before answering (Nkado, 1995). In this study, the possibility of bias was effectively lowered by selecting the sample carefully. The second problem was mitigated by sending the survey package to senior professionals, managers, and directors of organizations who were expected to have the professional commitment and morale to think through the questions carefully before answering them.

Concurrently, for testing the ANN models, a test data set containing information about five PPP projects was obtained from a panel of five experts. The experts were asked to respond to the survey questionnaire and each provide information of a PPP project. The profile of the experts is shown in Table 4. Their responses are deemed reliable. The results based on the test data set when using ANN technique were compared with those using MLR technique (see Jin (2010)).

4. Modelling risk allocation decision-making using ANN

In this section, how different models using ANNs were developed based on the theoretical frameworks, trained using BP algorithm, and tested by project data collected in individual interviews are reported. The entire process was carried out using MATLAB® software.

4.1. ANN model construction

An artificial neural network (ANN) is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use (Lin and Lee, 1996). It adopts non-parametric regression estimates made up of a number of interconnected processing elements between input and output data (Han and Diekmann, 2004). 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), modelling 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 risk allocation decision-making in construction projects.

In this study, typical three layered back-propagation ANN models were established to model the risk allocation decision-making mechanism. Each of the ANN models consisted of an input layer, a hidden layer, and an output layer. The input layer has six nodes, which represent the six independent variables. The output layer has one node, which represent the single *DV*. The number of nodes in the hidden layer was determined by trial and error to achieve more accurate performance of ANN models. The architecture of the ANN models is demonstrated in Fig. 2. The transfer functions of

Table 4
Profile of expert panelists.

	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 (No.)	12	16	10	8	18

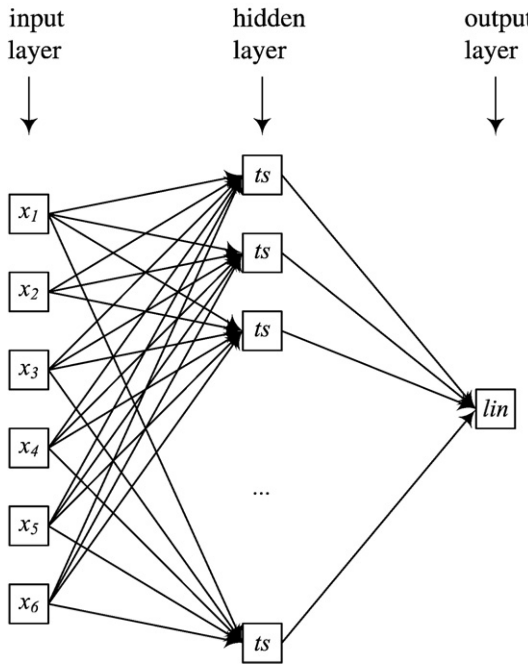

Fig. 2. Architecture of ANN models.

hidden and output layers are tangent-sigmoid and linear, respectively.

4.2. ANN model training

One major concern of ANN training is the stability-plasticity dilemma. Although continuous learning is desired in ANN, further learning will cause the ANN to lose its memory when the weights have reached a steady state (Haykin, 1999). In this study, the training set was thus partitioned into two disjoint subsets, i.e. the estimation subset used for model selection and the validation subset used for model validation. The *early stopping* method and the *leave-one-out* method, both of which are variants of cross-validation, were combined and used for ANN training.

Cross-validation is a standard statistical tool (see Geisser (1975) and Stone (1974) for detailed discussion). In the context of back-propagation (BP) learning, cross-validation provides an attractive guiding principle (Haykin, 1999). The *early stopping* training method was used to identify the beginning of overfitting (Amari et al., 1996b) because this method has been proved to be capable of improving the generalization performance of the network over exhaustive training (Amari et al., 1996a). The *leave-one-out* method, which is an extreme form of multifold cross-validation (Haykin, 1999, p.218), was used to tackle the constraint of limited available data set in this study. Accordingly, 43 (i.e. 44-1) data pairs were used to train a 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 squared errors under estimation and validation were then averaged over the 44 rounds of training. The related training performance indexes, i.e. *RMSE* (root mean squared error), are defined as follows:

$$RMSE_{est}^{(i)} = \sqrt{\frac{\sum_j \left(T_j - O_j\right)^2}{n-1}}, \quad (1)$$

$$RMSE_{val}^{(i)} = |T_i - O_i|, \quad (2)$$

$$RMSE_{est}^{avg} = \frac{\sum_{i=1}^{n} RMSE_{est}^{(i)}}{n}, \quad (3)$$

$$RMSE_{val}^{avg} = \frac{\sum_{i=1}^{n} RMSE_{val}^{(i)}}{n}, \quad (4)$$

where est=estimation; val=validation; avg=average; n=44, i.e. the number of training data pairs; T_i/T_j and O_i/O_j are the ith/jth target output and calculated output, respectively; $j \in \{1, \ldots, i-1, i+1, \ldots, n\}$.

The Levenberg–Marquardt algorithm was used as the training algorithm because this algorithm appears to be the fastest method for training moderate-sized feed-forward neural networks (Demuth et al., 2007). The maximum training epochs were set at 500. Starting with one node in the hidden layer, the ANN model was trained and analyzed. Each time, the number of hidden nodes was increased by one. If the estimation performance of the networks with one more hidden node (i.e. $n+1$) was better than that of a previous one (i.e. n), the number of hidden nodes was further increased. If the estimation performance of two consecutive networks with one and two more hidden nodes (i.e. $n+1$ and $n+2$) was both worse than that of a previous one (i.e. n), the training process stopped and the optimal number of hidden nodes was set at n. Accordingly, the optimal ANN structure was established. In total, eight ANN models with different number of hidden

Table 5
Training results of ANN models regarding R_O.

Network	$RMSE_{est}^{avg}$	$RMSE_{val}^{avg}$
6-9-1	0.6888	1.6408
6-8-1	0.6132	1.6446
6-7-1	**0.4150**	1.6437
6-6-1	0.4961	1.6182
6-5-1	0.5103	1.6594
6-4-1	0.5763	1.6161
6-3-1	0.6777	1.6125
6-2-1	0.8106	1.5888
6-1-1	0.7846	1.5989

nodes were trained. The training results are shown in Table 5. It can be seen that the ANN model with six input nodes, seven hidden nodes, and one output node (6-7-1) has the best estimation performance (see the datum in bold in Table 5). However, the error under validation is not small.

4.3. ANN model evaluation

The data set obtained from the expert panel was used as a test set in this study. The ratings of the six independent variables for each case were fed into the 6-7-1 ANN model. The forecasted efficient risk allocation strategies by the model were compared to the actual efficient risk allocation strategies specified by the interviewees. The evaluation performance of the model was determined by, besides *RMSE*, *MPE* (mean percentage error) and *MAPE* (mean absolute percentage error). *MPE* is an indicator of whether a model has a greater tendency to over- or under-forecast. *MAPE* is a good measure of the magnitude of the errors of forecasts. They are defined as follows:

$$PE_i = \frac{T_i - O_i}{T_i} \times 100\%, \tag{5}$$

$$MPE = \sum_{i=1}^{n} PE_i / n, \tag{6}$$

$$MAPE = \sum_{i=1}^{n} |PE_i| / n, \tag{7}$$

where PE = percentage error; and $n = 5$, i.e. the number of test data pairs.

The results of model evaluation are shown in Table 6. The *MPE* and *MAPE* of the ANN model are −3.4472% and 19.3632%, respectively. These two indexes reveal that the ANN model may have the propensity to over-forecasting although not much and, averagely, may contain less than 20% error in the forecast. The RMSE is 0.3415 and has been improved compared with that of MLR models (see Jin (2010)). That is to say, for instance, when an efficient risk allocation strategy for R_O is supposed to be 'equally shared by partners' (or 3 on a five-point Likert scale), the ANN model generally gives a forecast of 2.66 or 3.34. Given the subjective nature of the judgements by the respondents and interviewees, it can be concluded that the developed ANN model is valid and robust and has captured the essential components of the underlying nonlinear and complex dynamics.

Table 6
Evaluation results of 6-6-1 ANN model regarding R_O.

Performance Index	Value
RMSE	0.3415
MPE (%)	−3.4472
MAPE (%)	19.3632

5. Conclusion

Public–private partnerships (PPP or P3) have been adopted by governments in more and more countries as a preferred procurement method for public infrastructure projects. In PPP projects, many risks traditionally retained by government are transferred to private sectors. While risk transfer is a major driver for value-for-money, its practice has been deemed controversial and problematic. Optimal or efficient risk allocation (risk allocation) is thus of critical importance to the success of PPP projects. Consequently, it is worthwhile to investigate the mechanism that underlies the formation of optimal risk allocation strategies in PPP projects.

In this paper, a theoretical framework for modelling the risk allocation decision-making process based on the transaction cost economics (TCE) and the resource-based view (RBV) of organizational capability is revisited. However, conventional modelling techniques such as multiple linear regression (MLR) have been found unsuitable for complex and nonlinear problems like this. In this paper, artificial neural network (ANN) technique was adopted for modelling the risk allocation decision-making process. Training and test data were obtained in an industry-wide survey and from an expert panel, respectively. Due to the small number of data pairs, a number of cross-validation methods were used to ensure good generalizability of the ANN models.

The training and evaluation results show that the selected ANN model is satisfactory for modelling risk allocation decision-making. The empirical evidence further verifies that it is appropriate to utilize transaction cost economics and resource-base view of organizational capability to interpret risk allocation decision-making process. It is recommended that, based on the empirical results shown in this paper, in addition to partners' risk management mechanism maturity level, decision-makers, both from public and private sectors, should also seriously consider influential factors including partner's risk management routines, partners' cooperation history, partners' risk management commitment, and risk management environmental uncertainty. The decision on how much risk to transfer to the private partner should not be driven by partner's risk management capability or attitude alone. The decision should be made complying with TCE. All the identified factors influence the formation of optimal risk allocation strategies by their interacting effects. It may, for example, be cost-efficient to transfer more risk management responsibility to a private partner with higher risk management 'routine', higher commitment, longer cooperation history with the public partner, more mature organizational risk management mechanism, and higher certainty of some major environmental factors. However, due to the complex interacting effects among these factors, the implementation of an ANN approach in this study is well justified.

This paper makes an original contribution to the general body of knowledge on risk management in construction projects, in particular, on risk allocation in large scale infrastructure projects in Australia adopting the procurement method of public–private partnership (PPP). Moreover, this paper innovatively applies the artificial neural networks technique to modelling risk allocation decision-making process, on which previous research has barely focused. Nonetheless, due to the uncertain and incomplete nature of PPP projects, future research may integrate techniques such as fuzzy logic to design more intelligent models that are able to generate more accurate forecasts.

Appendix A. A sample of survey questionnaire

Section 1. Profile of You and Your Organization

1.1 Your total **experience** in the construction industry? _________ years
1.2 How many PPP **projects** have you worked on? _________ projects
1.3 Which **organization** are you now working for? _____________
1.4 What is the level of your **present position**? _____________
1.5 How many **PPP projects** has your organization worked on? _________ projects

In Section 2, please provide ***true and reliable*** *information about* ***a PPP project*** *that you* ***have appropriate involvement and/or knowledge in.***

Section 2. Project and Risk Management

2.1 **Project value** (approx.): AU$ _________ million
2.2 Project **concession** duration (post commissioning): _________ years
2.3 What **infrastructure sector** is the project categorized into? _____________
2.4 What is the **procurement** method for the project? _____________
2.5 What **role** does/did your organization play in the project? _____________
2.6 Before this project, how many project(s) have the government agency and the leading members of private consortium **cooperated** in? _____________
2.7 How many private consortia have been short-listed for **contract negotiation**? _________
2.8 In the table below, regarding the **situation of environmental factors** when partners were deciding risk allocation strategies, please indicate the extent to which you agree with each listed statement.

No	Description of Situation	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	Government policies on infrastructure PPPs are consistent and stable	☐	☐	☐	☐	☐
2	Laws and regulations associated with infrastructure PPPs are incomplete and liable to change	☐	☐	☐	☐	☐
…	…	☐	☐	☐	☐	☐

2.9 Regarding each listed risk in the table below, please specify the approximate risk **proportion** that **could** be transferred from public partner to private partner AND would make the management of the corresponding risk the **most efficient** among all alternatives.

No	Description of Risk	0% - 20%	21% - 40%	41% - 60%	61% - 80%	81% - 100%
1	An unanticipated change in law, policy or regulations influences private party unfavorably	☐	☐	☐	☐	☐
2	Demand of contracted services is unfavorably below anticipation	☐	☐	☐	☐	☐
…	…	☐	☐	☐	☐	☐

2.10 Regarding the risks in the above table, please indicate the extent to which you agree with each listed statement about the **PUBLIC** partner (*Pub*) in this project.

No	Statement	Change in law, policy or regulations					…					…				
		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	Before this project, *Pub* has gained ample experience in managing this risk	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
2	*Pub* has an established identification mechanism for this risk	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
…	…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

2.11 Regarding the risks in the above table, please indicate the extent to which you agree with each listed statement about the **PRIVATE** partner (*Pri*) in this project.

No	Statement	Change in law, policy or regulations					…					…				
		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	Before this project, *Pri* has gained ample experience in managing this risk	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
2	*Pri* has an established identification mechanism for this risk	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
…	…	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

This is the end of the questionnaire. Thank you very much for your time and participation.

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