Modelling capability based risk allocation in PPPs using fuzzy integral approach

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Abstract: Appropriate risk allocation and sharing are significant critical success factors for public-private partnership projects, but evidence suggests that poor risk allocation practices prevail. This signifies the need to develop a robust model for assisting stakeholders in risk allocation decision making. A non-additive fuzzy integral based multiple attribute risk allocation decision approach is proposed to effectively aggregate each stakeholder's risk management capability assessment on accepted risk allocation principles that are derived from qualitative judgements and experience based knowledge of experts. Data collected from privately financed and developed power and transport infrastructure projects in Pakistan are used to demonstrate and validate the model for key risk factors that exhibit variable risk allocation preferences. Comparison of results with an additive aggregation approach confirms suitability of the adopted methodology as it performs better when modelling risk allocation preferences of experts due to its ability to handle interdependencies in the risk allocation criteria. Apparently, the allocation and sharing of key risks is significantly influenced by market, sector and project contexts.

Keywords: decision making model; fuzzy set theory; fuzzy integral; infrastructure public-private partnerships; risk allocation.

Introduction

Risk allocation refers to the process of deciding who among the contracting agents (public and private sector partners) will shoulder the financial gain or loss in the event of a change in value from the estimated baseline (APMG International 2016a). In a public-private partnership (PPP) contract (vis-à-vis a conventional contract) all project risks rest with the private sector except those that are explicitly retained by the public sector (Federal Highway Administration 2013). PPP projects therefore require an adequate and clear allocation of complex risks. Appropriate risk allocation (*transfer* to private partner or *retention* by public partner) and *sharing* is identified as the most reported critical success factor for PPP project implementation (Osei-Kyei and Chan 2015). It directly influence the ability of, and prospects for, primary stakeholders to achieve their expectations with reference to their individual perspectives on risks (grantor: value for money and affordability, sponsor/investor(s): return on equity, lender(s): timely repayment of debt) (Grimsey and Lewis 2002, Darvish et al. 2006, Yescombe 2007, Oranization for Economic Co-operation and Development 2008, Pantelias and Zhang 2010, European PPP Expertise Centre 2012). A fundamental principle governing risk allocation is to apportion risk to the party that has the best ability to manage it. Where none of the parties has a superior ability or comparative advantage in managing a risk, then it should be shared (Asian Development Bank 2000, Irwin 2007). Although this principle seems appropriate, its exact application is difficult due to its vagueness. Moreover, Ng and Loosemore (2007) argue that multiple factors can influence the distribution of risks, including: debt providers' requirements; bargaining power; commercial requirements; economics; and company culture and policies. Appropriate application of risk allocation principles determines if a project will be bankable and whether it will remain viable throughout the long-term contract (GI Hub 2016). For PPP projects, it is sub-optimal for the public sector to inappropriately retain or transfer risks (Arndt 1999). Appropriate risk allocation offers several advantages including value for money (VfM) (Organization for Economic Co-operation and Development 2008, Asenova 2010). Poor risk allocation may result in issues such as higher risk premiums and conflicts and disputes on projects (Zitron 2006, Ng and Loosemore 2007). Despite its importance, multiple studies have indicated inadequate risk allocation practices on PPP projects (Arndt 2000, Zou et al. 2008, Marques and Berg 2011, HM Treasury 2012, Vassallo et al. 2012).

Whilst existing models and frameworks have contributed significantly towards the superior understanding, approximation and prediction of risk allocation and sharing in PPPs, there remains a need to further advance and develop a decision support model that better conforms to the preferences of decision makers and experts. This will assist the key stakeholders in achieving a workable and appropriate solution at the project development stage. Contextual factors also require consideration as it is widely acknowledged that risks and their management are influenced by country, infrastructure sector and project contexts (Mazher et al. 2017). Hence, a methodology that can help public and private sector experts to evaluate risks for allocation or sharing on an individual project basis would be extremely useful. The risk allocation decision process can be likened to a multiple attribute decision making (MADM) problem where a utility function can be employed to aggregate the risk management capability (RMC) ratings for risks across identified risk allocation criteria (RAC) in order to obtain an overall risk management capability index (RMCI) rating. This process can assist in evaluating multiple risks and identifying which party possesses sufficient overall RMC, thus informing the risk allocation decisions on projects. The process is subjective and implicit and requires qualitative judgement and experiential knowledge of experts (Lam et al. 2007, Ameyaw and Chan 2016). Additionally, the criteria employed may interact, which could be due to correlations, substitutiveness/complementarity or preferential dependence (Marichal 2000a). Arithmetic mean and simple additive weighting are commonly employed aggregation procedures, however they are unable to account for criteria interactions (Rowley et al. 2015). Ignoring these potential interactions may lead to contestable results (Grabisch 1996, Feng et al. 2010, Yu et al. 2015). A fuzzy integral based on a non-additive measure, such as the Choquet integral (Choquet 1953), can be applied as an aggregation operator for situations where the criteria interact. This consideration allows better approximation of decision makers' preferences by providing a mechanism to control the level of contribution of each criterion in aggregated evaluations, based on the nature of underlying interactions among the criteria.

Given the subjective, multi-attribute and context specific nature of the risk allocation and sharing problem, the objective of the research reported in this paper is to propose and validate a methodology to assist experts in risk allocation decision making for PPP infrastructure projects. The proposed model is based on the RMC paradigm and incorporates methods to accommodate subjective uncertainty (fuzziness – ambiguity of semantics) and aspects of criteria interaction. The RAC and key risk factors for risk allocation and sharing decision assessment (that lack consensus on allocation and sharing strategy and thus may be difficult to apportion) were selected based on extant literature and experts' opinions. Additionally, the research also strives to understand why certain risks (if any) may be allocated differently across projects. Aggregation approaches that employ additive and non-additive measures were applied to compare and explore how interactions may influence the assessments for risk allocation decision making. The developed model was further validated using data from two PPP projects in Pakistan from within the power and transport infrastructure sectors thus also providing unique insights regarding sectoral practices and any underlying differences.

Literature review

Risk allocation in PPP projects

Using risk allocation literature, Ameyaw and Chan (2016) classify existing risk allocation models/frameworks into two categories. The first category attempts to understand preferred risk allocation through the dominant or majority opinions and preferences of decision makers or their risk perceptions and attitudes. The difficulty of a risk allocation decision where there are differences in perceptions regarding risk criticality and RMC of parties may render majority preferences and opinions ineffective. The second category encompasses decision support or expert systems and utilizes a more critical approach. Specifically, it adopts theoretical frameworks (based on stakeholders' capability or transaction cost economics and the resource-based view of organizational capabilities) and various modelling approaches (game theory, artificial neural networks, fuzzy logic, multiple linear regression and fuzzy synthetic evaluation (FSE)). The review exposes various limitations of the available approaches and models which led the authors to present an FSE-based risk allocation model for water infrastructure PPP projects. Some important risk allocation research not covered in the review includes models developed for: risk allocation in construction contracts using the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach (Khazaeni et al. 2012); risk allocation in Malaysian PPP projects using the multi-objective optimization method (Alireza et al. 2014); identification of shared risks in PPP projects via application of a hybrid fuzzy cybernetic analytic network process model (Valipour et al. 2016); and PPP risk allocation evaluation based on the alternating offer bargaining game model (Li et al. 2017). In all of the decision support or expert systems, except for the game theory based research which models the bargaining process, the models predict optimum risk allocation strategy based on an assessment of the various parties' suitability to carry risk (determined from the RMC paradigm or other theoretical frameworks). This is achieved while employing different analytical approaches. In comparison to FSE and TOPSIS, most of the analytical approaches (including artificial neural networks, multiple linear regression, fuzzy logic and analytical network process) may require relatively more information to be input, either to implement or to effectively and adequately model the underlying decision problem. Both FSE and TOPSIS based risk allocation MADM models, though easier to implement, rely on aggregation operators based on additive measures which assume the RAC to be independent.

Arndt (1999) argues that the real world is more complicated than that which can be modelled by any theoretical framework. The following factors may all influence risk management (Arndt 1999): variations in description and meaning of risks as understood by each party; interpretational issues regarding terms for risk sharing mechanisms; differences in the views of parties regarding their ability to control and manage risks; and depth and maturity of the market for private infrastructure. A decision support model needs to be capable of adequately representing public and private sector preferences with regards to risks on individual projects. This will enable the model's output to accurately reflect stakeholders' distinctive perceptions, understanding and concerns, with respect to their capability and the allocation and sharing of each risk on the concerned project. Existing models frequently employ methodologies where, to some extent, the inputs from experts for model development and/or application are treated independent of their sector affiliations (public or private), thus there is a need to explicitly and adequately recognize this constraint in further research.

Risk allocation criteria and risk management capability

Abrahamson (1973) provides five principles that should be considered when allocating risks in construction projects. The principles reflect on a party's ability in terms of: risk control; risk mitigation; incentive/threat of benefiting/losing from risk; and prospects of achieving efficiency from allocation (interpreted as resulting in low risk premium) (NPWC/NBCC Joint working Party 1990). For PPP projects, perhaps one of the most insightful accounts of the principle of risk allocation based on the ability paradigm is provided by Irwin (2007). In order to maximize the total project value, a risk should be allocated alongside the right to make necessary decisions to the party in consideration of its ability to (Irwin 2007): influence the risk factor; influence the sensitivity of total project value to the risk factor (anticipate and respond to risk); and/or absorb the risk (depending upon available opportunities for: diversification, absorbing the risk at low cost, spreading risk and influence of risk attitude/preference). An individual party may not be best suited to managing a particular risk when these three aspects are considered simultaneously, so that tradeoffs may be potentially required to enhance the total project value. Several studies exist in academic literature which demonstrate the efforts that have been made to break down and define the ability maxim in order to achieve efficient risk allocation (Arndt 2000, Loosemore et al. 2006, Lam et al. 2007, Xu et al. 2010, Ameyaw and Chan 2016). This has resulted in development of criteria that can be used to assess a party's RMC. These criteria suggest common aspects with little difference. Representative RAC for PPP projects (Xu et al. 2010, Ameyaw and Chan 2016) are explained in sufficient detail in Table 1.

<Insert Table 1 here>

All the aforementioned criteria can apply to the RMC evaluation of both public and private sector stakeholders, except for the risk premium criterion as it attempts to determine reasonableness of premium paid for transferring risks from the public to private sector (Loosemore et al. 2006, Lam et al. 2007). The RAC require qualitative judgement and experience-based knowledge of experts to operationalize, as for example, the assessment of ability to control risk is hard to perform objectively, thus requiring the use of qualitative expert knowledge, natural language expressions and the application of fuzzy set theory (FST) (Lam et al. 2007). Furthermore, in multiple attribute decision analysis, the RAC may exhibit interactive effects due to the existence of potential tradeoffs. For instance, it is logical that a party well placed to influence a risk might not be as well suited to managing or absorbing it. A high overall evaluation of RMC should result only if a party is better suited to adequately managing a risk on all the requisite criteria. This situation cannot be modelled with additive measures where a poor performance/score on one criterion may be compensated or masked by a good score on another criterion, thus potentially resulting in a non-representative overall evaluation. With the use of fuzzy measures, it is possible to take into consideration the decision makers' preferences more holistically. These identified criteria can be employed in assessing and establishing the RMC of a party for individual risks so as to assist in decision making for risk allocation and sharing.

Fuzzy set theory

Zadeh (1965) pioneered the use of FST and introduced the concept of fuzzy sets in order to characterize and manipulate data that exhibit imprecision or non-statistical uncertainty. Let X be a classical set. A fuzzy set $\tilde{R}$ in X is defined by a membership function $u_{\tilde{R}}$: $X \rightarrow [0,1]$, which associates a real number in the interval [0,1] to each element x in X. The function value $u_{\tilde{R}}(x)$ defines the degree/grade of membership of x to $\tilde{R}$, which ranges from no membership (0) to full membership (1), with intermediate degrees of membership in between the two extremes. The concept of linguistic variables is employed as a means to approximately characterizing complex or ill-defined phenomena (such as in the case of humanistic systems) (Zadeh 1975a). Unlike a numerical variable, a linguistic variable's values (terms) are words or sentences in natural or artificial language; for example, the terms '*very important*' and '*extremely important*' may be used to assess the '*importance*' (linguistic variable) of an attribute or entity. The linguistic values can be represented by fuzzy numbers (Zadeh 1975b). Triangular and trapezoidal fuzzy numbers are used to manage the vagueness by defining boundaries/intervals instead of crisp values (Trivedi and Singh 2017). For a triangular fuzzy number (TFN) $\tilde{R}$, its membership function $u_{\tilde{R}}(x)$ can be expressed as (van Laarhoven and Pedrycz 1983, Hsieh et al. 2004):

(1) $$u_{\tilde{R}}(x) = \begin{cases} (x-L)/(M-L), & L \leq x \leq M, \\ (U-x)/(U-M), & M \leq x \leq U, \\ 0, & Otherwise, \end{cases}$$

Where, for the TFN, $\tilde{R}$, L, M and U are the lower, modal and upper values, respectively. The TFN is denoted as $\tilde{R} = (L, M, U)$. Let $\tilde{A}$ (L_1, M_1, U_1) and $\tilde{B}$ (L_2, M_2, U_2) be any two TFNs. The arithmetic operations are expressed as (Chen and Hwang 1993):

Addition: $\tilde{A} \oplus \tilde{B} = (L_1, M_1, U_1) \oplus (L_2, M_2, U_2) = (L_1 + L_2, M_1 + M_2, U_1 + U_2)$

Subtraction: $\tilde{A} \ominus \tilde{B} = (L_1, M_1, U_1) \ominus (L_2, M_2, U_2) = (L_1 - U_2, M_1 - M_2, U_1 - L_2)$

Multiplication: $\tilde{A} \otimes \tilde{B} = (L_1, M_1, U_1) \otimes (L_2, M_2, U_2) = (L_1L_2, M_1M_2, U_1U_2)$ for $L_i > 0$, $M_i > 0$, $U_i > 0$

Division: $\tilde{A} \oslash \tilde{B} = (L_1, M_1, U_1) \oslash (L_2, M_2, U_2) = (L_1/U_2, M_1/M_2, U_1/L_2)$ for $L_i > 0$, $M_i > 0$, $U_i > 0$

Fuzzy multiple criteria decision making

Bellman and Zadeh (1970) investigated the decision making problem in fuzzy environments and initiated work in fuzzy multiple criteria decision making. Given such a problem, consider a finite set of alternatives and evaluation criteria, represented by $A = \{a_1, a_2, \ldots, a_n\}$ and $X = \{x_1, x_2, \ldots x_m\}$ respectively (Marichal 2000a). Based upon the evaluations, each alternative a_j which belongs to A is associated with a profile of partial scores $h^j = \{h_1^j, h_2^j, \ldots, h_m^j\} \in \mathbb{R}^m$, where, for all i=1, 2, …, m, h_i^j represents the evaluation of alternative a_j with respect to criteria

x_i, with $h_i^j \in H_i \subseteq \mathbb{R}$. It is hypothesized that all the evaluations are given on the same interval scale to ensure commensurability (Kojadinovic 2007). A global score can be attributed to each of the profiles using an aggregation operator which takes into consideration the weights of importance of the criteria (w) (Marichal 2000a). For independent criteria, the most common aggregation operators are the weighted arithmetic means (WAM). The global score ($M_j(h)$) in this case is given by $M_j(h) = \sum_{i=1}^{m} w_i\, h_i,$ where $w_i \geq 0$ and $\sum_{i=1}^{m} w_i = 1.$ The global score can be used to rank alternatives or select the one that best satisfies the predefined criteria. For fuzzy problems, the global score $\tilde{M}_j(\tilde{h})$ can be obtained by calculating the summation of the product of relative fuzzy weight $\tilde{w}_i$ and the average fuzzy assessment value $\tilde{h}_i$, as (Tzeng and Huang 2011):

(2) $$\tilde{M}_j(\tilde{h}) = \sum_{i=1}^{m} \tilde{w}_i\, \tilde{h}_i$$

In a group setting, since several decision makers/experts provide criteria assessments, the mean operator is used to aggregate the experts' fuzzy assessments (Buckley 1985). Let $\tilde{R}_i^k$ denote the fuzzy assessment by an expert 'k' for any attribute 'i'. The average fuzzy assessment ($\tilde{R}_i$) for q experts will be:

(3) $$\tilde{R}_i = (\tfrac{1}{q}) \otimes (\tilde{R}_i^1 \oplus \tilde{R}_i^2 \oplus \ldots \oplus \tilde{R}_i^q)$$

Defuzzification operation can be performed to obtain a crisp number that adequately represents the fuzzy number. The most commonly used method (centre of area method) is employed here (Wang and Elhag 2007). For a TFN $\tilde{R}$, the defuzzified value (R') is given by:

(4) $$R' = \frac{\tilde{R}}{3} = \frac{L+M+U}{3}$$

Simple additive weighting (SAW) is the best known and most adopted MADM (additive aggregation) method. Fuzzy simple additive weighting (FSAW), which is an extension of the SAW method, is adopted in this paper (Chou et al. 2008, Lin et al. 2010, Tzeng and Huang 2011).

Fuzzy measure and Choquet integral

To accommodate interactions between criteria (given that the assumption of mutual preferential independence is rarely applicable), a monotone set function (μ: $2^m \rightarrow \mathbb{R}$) on X, called capacity (Choquet 1953) or fuzzy measure (Sugeno 1974), can be substituted to the weight vector (w) (Grabisch et al. 2008). A fuzzy measure satisfies the conditions: $\mu(\varphi) = 0$; $\mu(X) = 1$; and $\mu(S) \leq \mu(T)$ for all $S \subseteq T$ (monotonicity). The use of fuzzy measure (μ) allows modelling of the importance of each criteria and subset of criteria (Grabisch 1996, Marichal 2000a). In such a context, a natural extension of the WAM is the Choquet integral with respect to the defined fuzzy measure. The interaction phenomena (dependence) among criteria is of several types, including: correlation, substitutiveness/complementarity and preferential dependence (Marichal 2000a). Two criteria are said to be complementary if the importance of the pair is large while the importance of either one is rather low. For substitutive criteria, the union of two criteria is not too significant and the importance of the pair might be approximately the same as the importance of a single criterion (Marichal 2000a). The Choquet integral of $h^j \in \mathbb{R}^m$ w.r.t μ is given by:

(5) $$C^{\mu}(h^j) = \sum_{i=1}^{m}(h^j_{(i)} - h^j_{(i-1)})\mu(H_{(i)})$$

Where h^j are sorted in ascending order and $H_{(i)} = \{x_{(i)}, \ldots, x_{(m)}\} \subseteq X$ that includes only those criteria for which the score of the alternative a_j is at least equal to its score on x_i.

Fuzzy measures applications are curbed due to the exponential complexity that arises from the need to determine 2^m parameters (Kojadinovic 2007). Direct and indirect techniques can be employed to obtain these parameters. Direct elicitation of fuzzy measures from decision makers for large X is unlikely (Grabisch 1996, Marichal and Roubens 2000). Indirect techniques can be employed where the decision maker is able to provide certain preferences from which measures compatible with these preferences can be obtained. In order to reduce the number of parameters to be solicited from the decision maker, and to enhance their interpretation and understanding, Grabisch (1997) introduces the concept of the k-additive measure. Also, because it is easier for the decision maker to provide preference information on interactions between criteria pairs of two, this paper considers 2-additive measures only. The learning data (initial preferences of the decision maker) from which μ is to be determined consists usually of: a partial weak order over the set of alternatives; a partial weak order over the set of criteria; intuitions about importance of criteria; intuitions about interaction of criteria etc. (Marichal and Roubens 2000, Kojadinovic 2007, Grabisch et al. 2008).

The behaviour of Choquet aggregation and the fuzzy measure modelled interaction phenomena can be interpreted by several numerical indices (Marichal 2000b, 2004) which include the importance index and interaction index. For a given Choquet integral based model, if the analysis of these indices shows a discrepancy as opposed to the decision makers' reasoning, the initial preferences are enriched incrementally by additional constraints until a satisfactory model is found (Grabisch et al. 2008). Most fuzzy measure identification methods can be specified as optimization problems with specific objective function and the preferential information requirements. It should be noted that the preference information provided by the decision maker can only constitute a region of feasible/admissible fuzzy measures. Additional selection principles or constraints are employed to identify the most desired fuzzy measures (Wu et al. 2014). From the various methods available that are discussed by Grabisch et al. (2008), the minimum variance method was adopted because it favours the least specific capacity (if any) i.e., the one for which the Choquet integral is closest to the simple arithmetic mean and leads to a unique solution (Kojadinovic 2007, Grabisch et al. 2008).

Research methodology

The research began with a literature review of risk allocation in PPPs along with a brief exploration of existing models and methods for supporting risk allocation and sharing decision making on projects. Applicable RAC for each party were initially extracted from the literature (Table 1). A review of the PPP risk allocation literature (Irwin 2007, Ke et al. 2010a, 2010b, GI Hub 2016) complemented by discussion with industry experts highlighted several risk factors that exhibit the diversity of experts' preferences/opinions, hence creating the lack of a clear consensus on their allocation and sharing strategy. A list of 22 such risk factors was initially identified from the review; these factors were presented to five experts in a round of semi-structured interviews. The interviews also covered various other aspects related to risk management in the context of PPP infrastructure projects in Pakistan that are reported separately. The experts were requested to supplement the list of risks with their experience and to shortlist risk factors which are hard to allocate or for which the allocation strategy is most sensitive to contextual aspects. This led to the identification of 17 pertinent risk factors that were selected and explored for allocation and sharing between the parties. These risks form part of a larger 45 factor risk register that was utilized to conduct a risk assessment study, the details of which are not reported in this paper. The selected risks include only those risks that are explicitly addressed in concession or project agreements. The approach allowed focus on those risk factors that are harder to allocate rather than focusing on those factors for which the allocation regime is more obvious (such as the construction risk which is almost exclusively a private sector concern in PPP projects). Relevant RAC extracted from the literature were also presented to the experts to obtain their feedback on adequacy and relevance to the research objective.

Case studies were undertaken on actual projects while fixing risk allocation as unit of analysis in this paper. According to Zhang et al. (2016), case studies are popularly adopted in PPP research as they provide a suitable and effective method for investigation of complex PPP features in the unique and sophisticated project specific context. Research data were obtained through an investigator-administered questionnaire. This allowed the researchers to explore the contextual details regarding allocation and sharing of project risks and the circumstances surrounding the decision making. The questionnaire solicited basic information on experts, the selected projects and specific information on actual risk allocation and the relevant information on RAC and RMC of the stakeholders. Prior to conducting the case based surveys, the questionnaire's structure and clarity of instructions within were refined based upon experts' feedback from a pilot study with experts from the interview panel. The data received was analysed using both FSAW and fuzzy measure and Choquet integral to determine the RMCI for both public and private sectors for each risk for the case study projects. Results obtained were then compared with actual allocation and sharing of risks on case study projects. Hence, a two-pronged validation of the proposed methodology was performed by comparing the results with a traditional additive aggregation approach and with actual project data. Underlying reasons for differences in adopted allocation and sharing strategies of some common risks on the two case studies were also investigated and discussed to establish the model's robustness.

Model development

The literature review helped to determine the constraints of existing methods and a new methodology is therefore proposed, wherein each party can independently operate the model to evaluate its RMC against each risk. It allows assessment of the RMCI of a party for individual risks, which can be then used to inform the risk allocation decision making process (Fig. 1). The process of synthesizing the RMCI involves integration of the expert RMC assessments made against each RAC for each risk, with weightings of RAC that reflect the relative importance of the criteria. As the research intends to incorporate interaction effects for risk allocation and sharing decision making, fuzzy measure and Choquet integral analysis was performed.

<Insert Figure 1 here>

In order to observe the differences between aggregation approaches based on non-additive and additive measures, the results from fuzzy measure and Choquet integral analysis were compared with those obtained from FSAW. The principal difference between the two methodologies is in the estimation and handling of the importance weights of the RAC. The entire evaluation procedure is composed of three stages, namely: preparation, expert elicitation and analysis. Whilst the RMC evaluations for risks across the RAC were obtained and treated separately for each case-study and stakeholder, the data on importance and ranking of RAC, and interaction among the RAC, were collected and aggregated for public and private sectors and used for formulation of the RMCI in both case study projects. This treatment of data is justified due to the underlying similarity of stakeholders' concerns related to the importance of, and interactive effects among, the RAC at organizational level (public and private sectors). The fuzzy measure and Choquet integral analysis was implemented using the Kappalab package (Grabisch et al. 2015) for the GNU R statistical system (R Development Core Team 2005).

Data collection

Two case studies were conducted based on the availability and willingness of experts to participate; both focused upon risk allocation, but one case study involved a power sector project while the other involved a transport sector project. Investigating risk allocation based on the RMC paradigm across different sectors provided an insight into how and why certain common risks are allocated differently. Secondary data were collected in the form of project documents and other related sources (where available). The power sector case study represented one of the early wind power projects in Pakistan (referred to as CS1). The project involved finance, design, construction, commissioning and operation and maintenance of a wind farm in the south. The project was procured on a build-own-operate (BOO) basis under a standard 20-year term. The second case-study project (referred to as CS2, also from Pakistan) involved revamp and modification work and operation of a brownfield, controlled-access highway project on a build-operate-transfer (BOT) basis. The project was awarded under a concession period of 25 years. One notable difference between the two sectors is that the power sector is regulated under government policy, which also has implications for the standardization of risk allocation regime, whereas this is not the case for highway infrastructure sector projects. Both case study projects were already operational at the time of conducting this research. Complying with ethical requirements of confidentiality, names of projects and participating people/organizations involved have not been declared. Experts from public and private sector organizations that were involved in delivering and managing the case study projects participated by providing information on the actual allocation of the selected project risks (Table 2). According to the experts, risk allocation and sharing strategies adopted on the two projects represented an efficient profile which was to the satisfaction of both the public and private sector stakeholders. Other inputs were also provided in terms of: individual assessments of the importance and ranking of RAC; interactions among the RAC; the perceived RMC on each RAC for risks relating to the projects under consideration; and ranking of risks with respect to the overall perceived RMC. This was in line with the requirements of the methodologies adopted in this paper. Participating experts were selected based upon their experience in delivering PPP projects and their association of having worked on the selected case study projects. All participating experts possessed substantial experience in delivering and managing PPP projects with an average PPP specific experience of 9.58 years. The experts retained senior positions in their respective organizations while serving in various capacities, such as: director; deputy director; assistant director; chief finance officer; finance manager; chief operating officer; unit head; and senior executive. For each project, six experts participated to render the needed assessments for the selected risk factors, with three representing interests of the private sector (project company/investors) and three representing the public sector authority. The linguistic terms (Table 3) and the associated TFNs were adopted based on consensus of the experts.

<Insert Table 2 here>

<Insert Table 3 here>

Data analysis and model implementation

Stage 1: Preparation

Preparation entailed the selection of risk factors that needed to be allocated as well as the relevant RAC upon which RMC would be assessed and identification of the committee/panel of expert decision makers (public and private sectors). The pertinent risks, relevant RAC with respect to each stakeholder and the panel members that participated have been discussed above.

Stage 2: Expert Elicitation

Expert elicitation was based upon collection of necessary information in relation to the analysis methodologies that were employed for RMCI assessment. For FSAW based analysis, first the relative importance of the individual RAC was assessed by experts using linguistic terms (Table 3). The linguistic assessments were converted into corresponding TFNs (Table 3) and aggregate importance assessments ($\tilde{w}_i$) were obtained for each RAC using Eq. (3) (Table 4). All experts were considered equally important. Experts also evaluated each risk against the RAC using the linguistic terms in order to declare their RMC; Eq. (3) was then adopted to obtain aggregate assessments of RMC ($\tilde{h}_i$) against all the RAC (i = 1, …, m) for each risk (j = 1, …, n). Application of the fuzzy measure and Choquet integral based approach required additional information which was also provided by the experts and included: RAC rankings (Table 4); initial partial weak orders or ranks of risk factors (Table 5) in terms of a party's perceived overall RMC (from high to low – this is to obtain the desired ranking of risks based on preferences of the experts in view of the collective RMC evaluations on all the RAC for all risks); and information on interaction effects among RAC (Table 6). Crisp values for importance ratings of the RAC were obtained using Eq. (4). Since 2-additive Choquet integral was employed, participating experts considered and provided interaction information on some pairs of RAC that were interpreted as complementary. For all the other pairs, the RAC were considered non-interactive (Table 6). The experts collectively agreed that none of the RAC pairs should exhibit a substitutive relationship.

<Insert Table 4 here>

<Insert Table 5 here>

<Insert Table 6 here>

Stage 3: Analysis

Analysis included assessment of the RMCIs of the stakeholders for each risk. The FSAW based RMCI was computed using a simplified version of Eq. (2). Firstly, normalized weights ($w_i = \frac{w_i'}{\sum_{i=1}^{m} w_i'}$) for each RAC were computed from the crisp importance ratings of the RAC ($w_1', \dots, w_m'$) (Table 4) and the corresponding weight vector ($W = [w_1, \dots, w_m]$) developed for each party, which represented the crisp normalized weights for all the RAC. Separate fuzzy rating matrices were established which represented public and private sector project stakeholders and contained the RMC assessments ($\tilde{h}_i$) on the relevant RAC in each row, for all risk factors. Hence, for each project, matrices of order n x m, i.e. 17x8 and 17x9 were formed containing all the fuzzy aggregated RMC assessments for the public and private party, respectively. The product of the fuzzy rating matrix and the weight vector was calculated to obtain the fuzzy score vector ($\widetilde{M}_j$), that contains the fuzzy RMCIs for all risks. These fuzzy values were then defuzzified using Eq. (4) to obtain the RMCIs for individual risk factors to aid interpretation and risk allocation and sharing decision making (Table 7) (for detailed instructions on application of FSAW, readers are referred to Chen and Hwang (1993), Lin et al. (2010) and Tzeng and Huang (2011)).

For fuzzy measure and Choquet integral analysis, the aggregated experts' RMC assessments were defuzzified first (Eq. 4) to obtain crisp values of the same. The defuzzified RMC values ($h'_1, \ldots, h'_m$) for all risk factors, along with information on RAC rankings shown in Table 4, initial partial weak orders or ranks of risk factors derived from experts (Table 5) and information on defined complementary interactions among some pairs of RAC (Table 6), were programmed into the Kappalab package (for instructions on usage of the application software, readers are referred to Grabisch et al. (2008)). The analysis was performed separately on data from public and private parties for each project. The application was used to calculate the fuzzy measures and corresponding Choquet integral (Eq. 5) to obtain the RMCI of each risk factor (Table 7) using the minimum variance approach (Kojadinovic 2007, Grabisch et al. 2008). Additional constraints were added to the initial preferences of the experts after examination of the calculated importance and interaction indices, in order to ensure that the obtained Choquet integral model accurately reflected the public and private sector experts' reasoning in each case (Grabisch et al. 2008).

The proposed methodology after evaluating the RAC assessments provided an overall RMCI that can be linguistically interpreted from *very low* to *very high*. The final allocation strategy could be interpreted in view of the RMCIs of each party for each risk, while considering efficiency. Using the same linguistic terms to represent the RMCI (RMC, Table 3), the calculated RMCIs were translated employing the methodology adopted by Yang et al. (2003).

<Insert Table 7 here>

Comparison of model outcomes and actual risk allocations

Theoretically, if both parties possess *moderate* RMCI ratings, risks could be shared. Risks could be allocated to a party that possesses a higher RMCI. Alternatively, if the capability ratings reside on the same side of *moderate* RMCI (either lower or higher), risks could also be shared (Asian Development Bank 2000, Irwin 2007, Ameyaw and Chan

2015). This would ensure that parties retain the incentive to influence the risks or reduce a project's exposure to risks and also that the party responsible is the most suitable carrier of risk based on its RMC.

Comparing the outcomes of fuzzy measure and Choquet integral analysis with FSAW (Table 7), it was evident that the former methodology modelled experts' preferences more closely. For most risk factors, it was apparent that the linguistic RMCI assessments obtained from both the methodologies were the same and agree with the actual allocation of risks, although the underlying numerical indices vary for both methods. Actual allocation of the risk factors 'public opposition' (RF05) and 'design/construction/operation changes' (RF17) for CS1, and 'payment risk' (RF13) and RF17 for CS2, were more accurately represented by the non-additive method. These risks were shared as both the stakeholders obtained moderate RMCIs. The risk allocation for 'supply, input or resource risk' (RF08) for CS2 was also more accurately modelled by the non-additive method which was allocated to the private sector as apparent from its relatively higher RMCI. Although for CS2 both parties exhibited moderate RMCIs for macroeconomic risks (i.e. 'inflation' (RF01), 'variation in foreign exchange rate and convertibility issues' (RF02), 'interest rate fluctuation' (RF03)), the risks were allocated to the private sector rather than being shared. This, although justifiable by the relatively higher numerical RMCIs of the private sector, indicates that the decision to share or allocate a risk to one party may require further consideration beyond the RMCI alone. The same could be said for RF01 for CS1. For some risk factors, including 'delay in project approvals and permits' (RF09) for CS1 and CS2 and RF05 for CS1, the preference was to share the risks rather than transferring to the party with a higher RMCI. However, the output from both methodologies did not refute the actual allocation as both parties possessed moderate to high RMCIs. Several reasons might explain these observations. On certain occasions a risk may be tolerable by the private partner at a reasonable price however the public party may be better positioned to handle the risk and therefore may consider taking it back or sharing it to some extent so as to realize increased VfM (APMG International 2016b). Similarly, some risks may be shared with the private party even if it cannot fully or accurately assess the risks, as it may be able to act by limiting risks' occurrence or limiting or mitigating risks' consequences. Yet in other cases, it may be reasonable to compromise on optimal risk allocation and VfM prospects to some extent in emerging or in less mature PPP markets to ensure the project's bankability and commercial feasibility by applying de-risking strategies (cf. APMG International (2016b) and World Bank (2017)). Risks may be shared or transferred to the private sector only where this brings efficiency. This is important because the size of the risk premium will depend to a large extent on the degree of uncertainty surrounding the risk and degree of risk aversion of the service provider (Arndt 1999). Quantitative assessment may be employed for better insights, however for a number of risks reliance on common practice and precedents, as well as exercising judgment, will be important since innovation and risk management capability are difficult to evaluate and some risks are unquantifiable, hence suggesting caution in quantitative assessment of VfM (APMG International 2016b). The model therefore aims to assist experts in negotiating an efficient allocation of risks on PPP projects rather than specifying general allocation strategies of risks which, as explained earlier, may not be optimum for all projects and situations due to contextual aspects (APMG International 2016b, GI Hub 2016). Overall, and for most risk factors, the consideration of interactions in RAC seems to provide more conservative estimates of RMCI. Further discussion on risk allocation and sharing on case study projects is made in relation to the results obtained from fuzzy measure and Choquet integral analysis.

Starting with the macroeconomic risks (RF01, RF02 & RF03), almost all of the stakeholders in both case studies exhibited a low to moderate ability to manage the risks. This is consistent with contemporary discourse (Arndt 1999, Irwin 2007). While governments are the primary decision makers on macroeconomic policy, and by that virtue hold a higher capability to influence these risks, there is an argument that governments should not be required to shape policies on such matters while constrained by project specific situations. Conversely, the private sector also holds a measure of control by potentially holding responsibility to finance, design, construct and operate and maintain the infrastructure assets. Thus, the extent of project exposure to macroeconomic risks can be potentially reduced by incorporating business acumen and various strategies that can partially hedge against the potential impacts. In addition, the quantum of risk itself can be an influential factor. For example, power infrastructure projects in Pakistan are more exposed to foreign exchange risks than transport infrastructure projects due to the large and expensive equipment imports involved and international investments. Unpredictable variances in the foreign exchange rate can be excessive for any private sponsor to manage, not to mention the potential difficulties in convincing investors to accept such a risk exposure. Hence, the difference between macroeconomic risk allocation practice across the sectors can be best explained by differences in stakeholders' risk attitudes/preferences, which are influenced by country and project specific contextual aspects. Apparently, macroeconomic risks rest best with the government, given the investment climate and current risk preferences of both the public and private power sector stakeholders in Pakistan. However, as the investment climate improves and investors show greater interest in establishing projects in the country, reassessment of the situation may dictate gradual transfer of macroeconomic risks to the private sector. For the transport infrastructure sector, the allocation of macroeconomic risks to the private sector falls in line with the recommendations discussed above and because of the relatively higher preference of the private sector to bear these risks. This could be the case due to the strong viability of the brownfield case study project where robust existing and forecasted demand projections may have encouraged the private sector towards a risk seeker attitude. Ke et al. (2010a) reported that a higher proportion of respondents favoured sharing of risk of inflation rate volatility in China, Hong Kong and Greece and allocation to private sector in the UK, whereas, for interest rate volatility risk, China, Hong Kong and the UK favoured more its allocation to the private sector while respondents from Greece provided a greater support for sharing the risk.

Four risks were shared in both the case-study projects, namely: 'public opposition' (RF05), 'delays in project approvals and permits' (RF09), 'insurance risk' (RF10) and 'design/construction/operation changes' (RF17). The estimated RMCIs for these risks matched well with the actual risk allocations with two exceptions. For RF05 in CS2 and RF09 in both case studies, the expectation would be to allocate them to the public sector due to their high RMCI. Level/intensity of opposition is an important indicator of who takes responsibility as small local issues fall within the management domain of the project sponsor, whereas politically influenced/social unrest at large scale becomes an issue away from its control, hence the public sector must manage it. The responsibility to obtain approvals and permits from various government authorities and departments falls upon both parties. Approvals, permits or licenses may be required in relation to land zoning, town planning, environmental and building standards and health and safety regulations (Rothballer and Gerbert 2015) and others related to project design and construction. Similarly, the party initiating any changes was considered responsible for bearing the impact, hence this risk was also shared. This is an important risk as changes are inevitable over long concession periods (Javed et al. 2014). RF10 was shared for CS1 with a cap defined at one percent of project cost. Any deviation over the cap would be absorbed by the project sponsor, however according to the experts, such a cap was not usually breached. For CS2, it was mostly carried by the project sponsor. In either case, if a risk becomes uninsurable, the project sponsors are not responsible for maintaining insurance.

Both 'supply, input or resource risk' (RF08) and 'payment risk' (RF13) were accurately modelled for CS2 by the proposed methodology. With regards to CS1, only the first batch of wind power projects in Pakistan were specifically given coverage for wind resource risk. This arrangement was necessary as the existing data on wind resource assessment was inadequate and not in accordance with the acceptable standards. Projects under the revised policy do not enjoy this coverage. For CS2, RF08 is a private sector concern as it is considered in a better position to control and manage the risk. Delays in payments by the power purchaser are compensated via adjusting the payable amount in proportion to a predefined interest rate as per provisions of the contractual agreement. For the CS2, the concessionaire is responsible for toll collection, however enforcement of the toll is the government's responsibility.

For the remaining risks, the model accurately estimated the RMCIs in comparison to actual risk allocations. For the 'land acquisition risk' (RF04), both stakeholders for CS1 expressed moderate to high RMCI, where the public sector RMCI was higher. In this particular case, the project site was selected by the public authority spearheading the project who was able to procure it beforehand. The project company expressed agreement that they could have taken up this risk, however it was not necessary due to the existing arrangements. For CS2, the initial right of way was already in place and the risk was related to land required for possible future expansion/new construction. Hence, RMC assessment similar to CS1 was observed with the public sector taking on the risk due to its higher RMCI which was as a result of its higher ability to influence the risk (Irwin 2007). 'Change in law/regulation risk' (RF06) was recorded exclusively in the domain of the public sector across both the projects. An argument exists that the private sector might retain some level of risk responsibility so as to influence the project's sensitivity as much as possible, and be less vulnerable to the effects of such changes (Arndt 1999, Irwin 2007). However, possibly due to the emerging status of the market in both the renewable energy and highway infrastructure sectors, and associated high risk averseness of the private sector, the government covers this risk. This concurs with the findings of Ke et al. (2010a) where respondents from Greece, Hong Kong and China (with relatively less experience in PPPs) exhibit a preference for the public sector sharing or undertaking legal risks, as opposed to the UK where few respondents indicated their preference to allocate legal risks to the public sector. RF06 would be shared in more mature markets, but bankability and affordability concerns (and potential erosion of VfM) in the context of emerging markets may require a full retention of this risk by the public sector (World Bank 2017). Risks related to 'geotechnical conditions' (RF11) in both case study projects were seen as fairly predictable due to the nature and scope of work in CS1; since CS2 was a brownfield project, the risk was perceived as predictable and low. In each case, the risk was allocated to the private sector. Risks related to 'financing' (RF12) were assumed by the project sponsors in both cases, as they were required to finance the projects. In case of CS1, the government's provision of guaranteed purchase of electricity and return on equity, and for CS2, strong project viability, made it possible for the project sponsors to easily secure the required financing. Both the 'latent defect risk' (RF14) and 'residual risk' (RF15) did not apply to CS1 as it is a greenfield project on a BOO basis. For CS2, both risks were allocated to the project sponsor who was considered in the best position to assess the situation before taking over the project and for building suitable strategies and costs in the estimates. For residual risk, the sponsor is contractually required to bring the project to a pre-specified state, as per handback requirements, before transferring it back to the government. Since CS1 project's applicable policy and energy purchase agreement provide for mandatory purchase of electricity, the 'demand risk' (RF07) was parked with the public sector. For CS2, given that it was a brownfield project with sufficient data on demand and confidence in strong forecasts, the private sector was willing to bear the risk. In both case study projects, the 'risk of competing facilities' (RF16) is retained by the public sector. For CS1, the mandatory purchase provision underpins the arrangement, whereas for CS2 the government will reimburse the project sponsor for potential losses in case any competing facilities are introduced in the future.

With reference to actual allocation and sharing of risks (Table 2), the results of the model (Table 7) and the discussion above, it is clear that the proposed methodology was able to closely approximate the experts' risk allocation preferences on case study projects. While the case studies discussed in this paper did not originally apply the proposed model for risk allocation and sharing decision analysis, the value of application of such quantitative analysis is to facilitate learning and appreciation of RMC differences among the parties with a view to enhance judgement in decision making. This can potentially save time and resources in risk allocation related contract negotiations and may even positively influence RMC perceptions of the parties as well as their risk attitudes. The model's application can assist relevant decision makers in achieving an efficient risk apportionment profile on projects to be undertaken in the future. This is particularly important as the issue of inappropriate allocation of risks on projects has been reported in literature (Arndt 2000, Zou et al. 2008, Marques and Berg 2011, HM Treasury 2012, Vassallo et al. 2012). Explicit and systematic deliberation over the identified RAC for each risk and the calculated RMCIs can highlight strengths and weaknesses of the involved parties, thus adequately informing decision making regarding risk allocation and sharing. This signifies the proposed method's potential to assist as a risk allocation and sharing decision support tool for PPP projects.

Conclusions

It is well established in literature that risks should be allocated or shared in accordance with the risk management capabilities of contractual parties. While this is easier to understand for some risks, contextual aspects (RMC, country/market, sector and project) make it difficult to define a standard for other risks. A list of 17 such risk factors was developed from extant literature and inputs from experts. A fuzzy measure and Choquet integral based multiple attribute risk allocation decision making model was proposed that employs explicit and accepted risk allocation principles. Two case study projects were investigated, one from the power sector and one from the transport infrastructure sector, for actual allocation of key risks and to demonstrate and validate the risk allocation and sharing model. The results show that a model capable of considering interactions among the qualitative RAC can assist stakeholders as a decision support tool and provide more representative results vis-à-vis models that rely on aggregation operators based on additive measures. Additionally, the discussion on differences in allocation and sharing strategies of specific risks across infrastructure sectors and projects provided insights into the underlying reasons and showed that for given risks, it may be viable (to secure VfM), and in some cases absolutely necessary, to determine a custom strategy over any standard approach. This is particularly important when the public sector has to adjust and make room for accommodating risk preferences of the private sector for the sake of building private sector confidence and for growth of the market. The methodology presented herein provides an explicit, structured and a comprehensive framework which can assist the stakeholders to efficiently allocate and share risks on projects by considering their risk management capabilities and also the contextual aspects.

While the fuzzy measure and Choquet integral model adequately predicted the actual risk allocation based on the RMC paradigm, the decision regarding when to share a risk between public and private sectors was often unclear and required consideration of specifics to determine the actual strategy. Furthermore, the proportion of risk sharing could not be determined from the model output. For each of these risk factors, the proportion of responsibility that is attributed to a party is strongly related to the nature of risk and different underlying scenarios which need to be investigated individually. This creates avenues for further research to develop mechanisms that guide the risk sharing proportion for the parties. More case studies may also be conducted in the future to further validate the applicability of the methodology for practical use. In addition, the method employed to estimate the values of fuzzy measures can be further advanced to model the decision makers preferences more accurately. It may also be useful to investigate the indicators of risk management attitude for public and private sector PPP stakeholders as it forms an important aspect in determining the RMC of a party and directly affects the risk allocation and sharing regime.

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Fig. 1. Fuzzy integral based risk allocation model.