Bayesian Analytics for Estimating Risk Probability in PPP Waste-to-Energy Projects

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Abstract: Appropriate risk analysis and management is critical to the overall success in public–private partnership (PPP) projects, in which one of the key issues lies in an accurate estimation of the risk occurrence probability. Traditionally, this probability is estimated either relying on experts' judgments or historical data. The estimation may not be accurate due to the subjective nature of the former and the data sparsity of the latter. In this research, a Bayesian analytic approach is taken to forecast risk occurrence probability, combining experts' judgments and historical data. This Bayesian approach consists of four main steps: (1) data collection, (2) modeling prior probability, (3) modeling posterior probability, and (4) multiupdating and analytics. This approach can achieve a more accurate estimation of risk occurrence probability compared with only relying on experts' judgments or historical data because the subjectivity of experts' judgments is mitigated by incorporating observed real data, and the data sparsity is supplemented by experts' judgments. This model is applied to forecast the probability of several critical risks in PPP waste-to-energy (WTE) incineration projects in China, and the results demonstrate its feasibility and applicability for targeted solutions in risk response and allocation. **DOI: 10.1061/(ASCE)ME.1943-5479.0000658.** *© 2018 American Society of Civil Engineers.*

Author keywords: Bayesian updating; Risk identification; Public–private partnership (PPP); Posterior probability; Waste-to-energy (WTE).

Introduction

Because of frequent energy security issues and public environmental awareness, the power generation programs from renewable energy sources have attracted growing support worldwide (Martins et al. 2011; Song et al. 2013). Municipal solid waste (MSW) is a renewable energy source, in which the amount of MSW is huge in many cities, particularly in developing countries, such as China. There are three main MSW treatment methods, including landfills, composts, and incineration (Li et al. 2016). Waste-to-energy (WTE) incineration is one of the most effective ways to change MSW into resources and reduce wasteland fills (Cheng and Hu 2010; Rand et al. 2000). The waste incineration rates in developed countries, such as Japan, Denmark, and Switzerland, are high, and the incineration rates reach up to 70–80%. The waste incineration rates in developing countries, however, are relatively low. For instance, the waste incineration rate in China is around 15–20% (Asian Development Bank 2007; Li and Zhang 2013).

A public–private partnership (PPP) is a very effective contractual arrangement between a private party and a government agency (Papajohn et al. 2011; Yuan et al. 2010; Tang et al. 2013; Soomro and Zhang 2016; Zhang and Xiong 2015; Wang et al. 2016), which has been widely applied in the development of numerous WTE power plants (Song et al. 2013). PPP attracts funds from the private sector to provide public works and services and to improve efficiency (i.e., shorter construction periods, lower construction and operation cost) (Song et al. 2018). Normally, in PPP projects, the private sector takes the responsibility of design, construction, operation, and maintenance and gets investment returns through user pays and/or necessary government payments (Shrestha et al. 2018; Xiong and Zhang 2016). The public sector is responsible for supervision on the price and quality of infrastructure and public service to guarantee the maximization of public interest (Dai and Lyu 2015; Soomro and Zhang 2015; Sha 2016; Li et al. 2016). It is widely accepted that, when exposed to risk, the private sector can achieve a higher level of efficiency, increasing the value for money of the projects (Cruz and Marques 2013a; de Castro e Silva Neto et al. 2016; Zhang and Ali Soomro 2016).

Despite the wide use of the PPP financing model for WTE incineration plants, many uncertainties affect the implementation of PPP projects (Xiong and Zhang 2014; Xu et al. 2015). Because of the large-scale investments, long concession periods, multiple participants, and staggered rights and obligations, there is an inherent variety of risks in PPP arrangements. A great number of risks have been identified during the PPP concession period in the literature (Kumaraswamy and Zhang 2001). For instance, Li et al. (2005) revealed 46 risk factors for PPP projects. Ke et al. (2010) presented a list of 37 risk factors associated with PPP projects in China. Cruz and Marques (2013b) indicated that contracts failing to address risks led to increasing costs for infrastructure services. Xu et al. (2015) identified five critical risk factors from 14 PPP WTE incineration plants through content analysis. Song et al. (2013) identified 10 key risks through interviews, surveys, and field visits and developed response strategies for risk mitigation from the perspectives of both public and private sectors. Hwang et al. (2013) noted that most PPP risks were difficult to control and analyze. Xiong et al. (2016) indicated that serious risks may occur during the long concession period, and a PPP project may have to be terminated early if such risks cannot be managed effectively. Overall, appropriate risk identification, analysis, and allocation of risks between public and private sectors were essential

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to the overall success of PPP projects (Jin and Doloi 2008; Zhang 2005a, b).

In this research, the main objective is to answer the question: How do we achieve a more accurate estimation of risk probability in PPP projects, given that the historical data are limited? To address this issue, an improved risk occurrence probability forecasting model for PPP projects is developed based on the Bayesian updating approach. It integrates the expert's judgment and the historical data available to reach a more reasonable estimation. The developed approach is applied to forecasting the occurrence probability of critical risk factors for PPP WTE incineration projects in China. Results from the case study demonstrate the feasibility and the applicability of the developed approach.

Literature Review on PPP Risk Analysis

The term *risk* is defined as the most likely consequence of a hazard, combined with the likelihood of occurrence probability (Zhang et al. 2014). An accurate estimation of the risk probability plays a significant role in the lean construction and management in PPP projects (Dikmen et al. 2012; Zhou et al. 2014). From the previously mentioned literature, most of the studies focused on the risk identification and classification (Song et al. 2013; Soomro and Zhang 2015; Xu et al. 2015), risk analysis and assessment (Zeynalian et al. 2013), and risk allocation and management strategies (Iossa and Martimort 2012; Karim 2011; Rebeiz 2012; Li et al. 2017; Mizutani et al. 2017). By using literature reviews, questionnaire surveys, case studies, and net present value at risk models, the studies mainly assessed the impact or harm degree of risk factors, without taking the likelihood of occurrence into great consideration. Very few studies investigated the updating mechanism of the risk probability in PPP projects. The traditional way of forecasting the risk occurrence probability is mostly based on the expert's estimation (Shahata and Zayed 2016) or based on the limited historical data of similar types of projects (Anastasopoulos et al. 2012). The experts' judgments are subjective in nature, which is a big threat to the estimation accuracy (Zhang et al. 2014). Because of the imperfection of the expert's judgment and the limitation of historical data, risk occurrence probability forecasting remains a research question that needs to be improved. This research attempts to explore the possibility of combining experts' subjective estimations and the observed real data for a more accurate estimation of the risk probability in PPP projects.

In the last decade, numerous research efforts have been devoted to exploring the risk management issue in PPP projects (Chan et al. 2011; Iyer and Sagheer 2010; Wang and Zhang 2017; Xu et al. 2015; 2010a). Several categories of risks in PPP projects are identified including (1) financial risks, including interest rate change fluctuation, exchange rate change, and inflation; (2) operational risks, including lower revenue than guaranteed (Ke et al. 2010) and cost overruns; (3) political risks, including inappropriate intervention (Maslyukivska and Sohail 2007) and government corruption (Medda 2007); and (4) environmental risks (Ng and Loosemore 2007). Zhang et al. (2005b) indicated that inadequate or inappropriate risk analysis and assessment was likely to lead to management dilemmas, such as financial difficulties, decision-making mistakes, schedule overruns, operation inefficiency, and others.

Typically, PPP risks can be classified into two big groups: systematic and specific. Systematic risks (e.g., political, social, economic, legal) generally stem from the external environment with little control of the private sector, whereas specific risks stem from inherent characteristics of the project itself. Indeed, the group of specific risks is more controllable for both the public and private sectors, which should pay much more consideration when analyzing risks in PPP projects. Currently, studies on PPP projects have covered a wide range of areas, including water treatment (Chen 2009), public venue, toll roads (Heravi and Hajihosseini 2012), and public housing (Abdul-Aziz and Kassim 2011). Little attention, however, has been given to PPP WTE incineration projects. Specific risks for the development of PPP WTE incineration projects, such as revenue issues, environmental problems, and technological shortcomings, are not sufficiently addressed in the literature.

Methods to analyze and assess risks in PPP projects can be broadly divided into three categories: qualitative (such as literature review, case study, and questionnaire survey), semiquantitative [such as analytic hierarchy process (AHP), game theory, and fuzzy synthetic evaluation], and quantitative methods [such as artificial neural networks (ANNs) and value for money]. For instance, Xu et al. (2010b) proposed a risk assessment model based on a fuzzy synthetic evaluation approach. Li and Zou (2011) developed a fuzzy AHP-based approach for risk assessment for PPP projects. Wu et al. (2017) identified 44 risk factors and 19 critical risk factors in straw-based power generation PPP projects by using a fuzzy synthetic evaluation approach, in which the integrated risk level was defined as the square root of the product of the likelihood of occurrence and magnitude of impact. In general, the experts' judgment data (through a questionnaire survey, case study, or checklists) are one of the most used data resources in PPP risk management. However, the subjectivity and fuzziness existing in this kind of data resource is one big challenge for achieving the accuracy of risk analysis and assessment (Elbarkouky et al. 2014).

The Bayes theorem uses a combination of a priori and posterior knowledge to model forecasting data, which allows explicit modeling of changes over time; therefore, it can model the evolution of the probabilistic dependencies in a complex system (Zhang et al. 2013). The Bayes theorem can considerably improve the quality of the input data even with only a small number of data sets collected in the early stages of a project's life cycle. Project designers can easily update the prediction when additional information or evidence is available (Špačková and Straub 2013; Zhang et al. 2014). The Bayesian updating approach is widely used in the field of civil engineering, and it is a useful methodology for updating the estimation of the parameters of the failure probability, in which both objective data based on the sample test and subjective judgments taken from the experts' opinions can be combined (Chung et al. 2006; Zhao and Fu 2006). For this reason, the Bayesian technique has been used for estimating and allocating risks in PPP projects. For instance, Cruz and Marques (2012) developed a Bayesian network approach to compute the variability in the public sector comparator to accommodate dynamic analysis to cope with uncertainty. Li and Ren (2009) presented a Bayesian technique framework for allocating demand risk between the public and private sector in PPP projects, which can help reduce the uncertainty in distributing the risk responsibility between both sides. In general, the Bayes theorem uses external observation to update the system outcome for a more accurate estimation. Thus, this paper investigates using the Bayesian theorem to develop an improved risk occurrence probability forecasting model for PPP projects.

Moving the existing research forward, the previously mentioned studies all contribute significantly to the body of knowledge and demonstrate the complexity and obscurity of PPP risks. Particularly, "subjectivity" and "accuracy" should be two big issues that need to be considered in PPP risk management. In this research, a Bayesian analytic approach is taken to forecast risk occurrence probability in PPP WTE projects, combining experts' judgments and historical data. This approach can achieve a more accurate estimation than merely relying either on experts' judgments or on historical data because the subjectivity of experts' judgments is reduced by incorporating observed real data, and the sparsity of historical data is supplemented by experts' judgments.

Methods

PPP WTE projects are subjected to a range of risks during the concession period, and these risks may arise from multiple resources, such as overrated revenues, environmental pollutions, technical shortcomings, and others. To improve the accuracy in the estimation of risk magnitude in PPP WTE projects, a risk occurrence probability forecasting model using the Bayesian updating approach (ROPFM-B) is developed in this research. The proposed methodology for estimating risk probability is based on a mixed approach of both expert judgments and historical data, combined via a Bayesian approach. Fig. 1 illustrates the workflow of the developed approach, which consists of mainly four steps: (1) risk identification and data collection, (2) modeling prior probability, (3) modeling posterior probability, and (4) multiupdating and analytics.

Step 1: Data Collection

The project risks should be first identified through preliminary studies by reviewing literature, standards, technical reports, and/or surveys. The identified risk checklist provides a basis for the input-output framework in this research. The input data needed in the developed ROPFM-B approach come from two resources: (1) the expert's judgments on the risk occurrence probability and (2) the historical data about the risk events in real cases. The expert's judgments can be collected through interviews or questionnaire surveys. We classify the expert's judgment on risk occurrence probability into several intervals, such as "$\theta = 0.1$, $\theta = 0.3$, $\theta = 0.5$, $\theta = 0.7$, and $\theta = 0.9$," and then compute the mean value among the surveyed experts. An example is later presented in the case study of this research. The historical information of risk occurring or not can be collected through the industrial records or cases. Fig. 2 illustrates the input–output framework of the proposed ROPFM-B approach in this research. If we use the model to forecast the occurrence probability of a risk factor, then the inputs of the expert's judgment on the probability distribution of the risk occurrence probability are used to model the prior probability. The information of whether the risk event that occurs or not in the real case will be used to update the prior knowledge to achieve the posterior knowledge. The output of this model is the result of estimated risk occurrence probability, which combines both subjective (experts' judgments) and objective (historical cases) data.

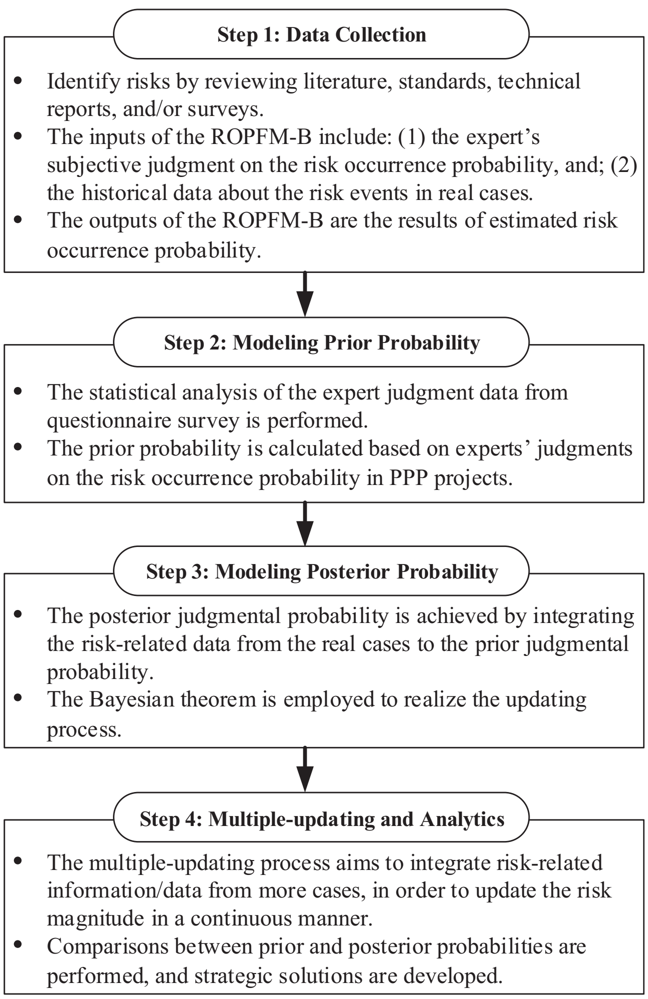

Fig. 1. Workflow of the developed ROPFM-B approach.

Step 2: Modeling the Prior Probability

For any risk factor, the probability of risk occurrence based on the expert's judgment is defined as the prior probability of the risk factor in the model, and is denoted as P'_r. P'_r is calculated through the probability mass function (PMF) based on the expert's judgment. PMF is the prior knowledge of the risk occurrence probability, which is defined as Eq. (1). Thus, the first step is to model PMF and calculate P'_r, as follows:

$$f'_R(r) = \begin{cases} P'_r(\theta_j), & r = \theta_j \\ 0, & \text{otherwise} \end{cases}; \quad 0 \le \theta_j \le 1; \quad j = 1, 2, \ldots, m \tag{1}$$

where $f'_R(r)$ = prior knowledge (PMF) on the risk occurrence probability; R = random variable (represents the risk); $P'_r(\theta_j)$ = prior probability on the mean value of θ_j for the risk occurrence; θ_j = jth estimated mean value of the occurrence probability; and m = number of the estimated mean values of the occurrence probability given as the choices in the questionnaire.

PMF is given based on the expert's judgment. Specifically, during the questionnaire survey or expert interview, a group of the risk occurrence probabilities, denoted by θ_j, are provided as choices to collect the expert's views. Then, the mean values are approximately regarded as an estimation of the expert's judgment on the risk occurrence probability. The prior probability distribution of the risk factor can be obtained by using Eq. (2)

$$P'_r(\theta_j) = \frac{NP_r(\theta_j)}{NP}; \quad 0 \le \theta_j \le 1; \quad j = 1, 2, \ldots, m \tag{2}$$

where $P'_r(\theta_j)$ = prior probability on the mean value of θ_j for the risk occurrence; θ_j = jth estimated mean value of the occurrence probability given as the choice for the risk factor in the questionnaire survey; $NP_r(\theta_j)$ = number of respondents who select θ_j for the risk

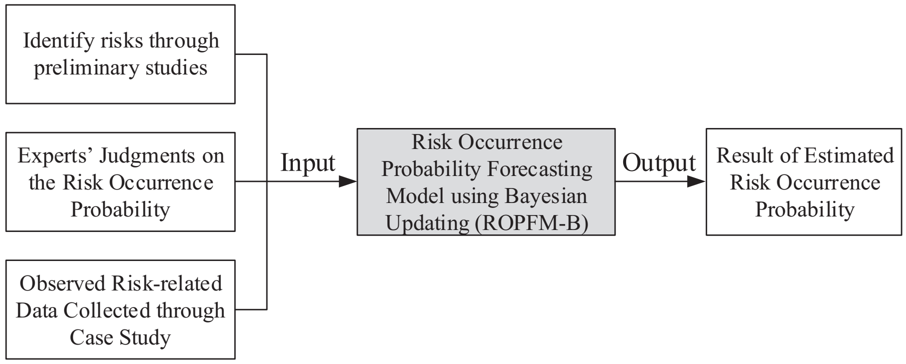

Fig. 2. Input–output framework in the proposed ROPFM-B approach.

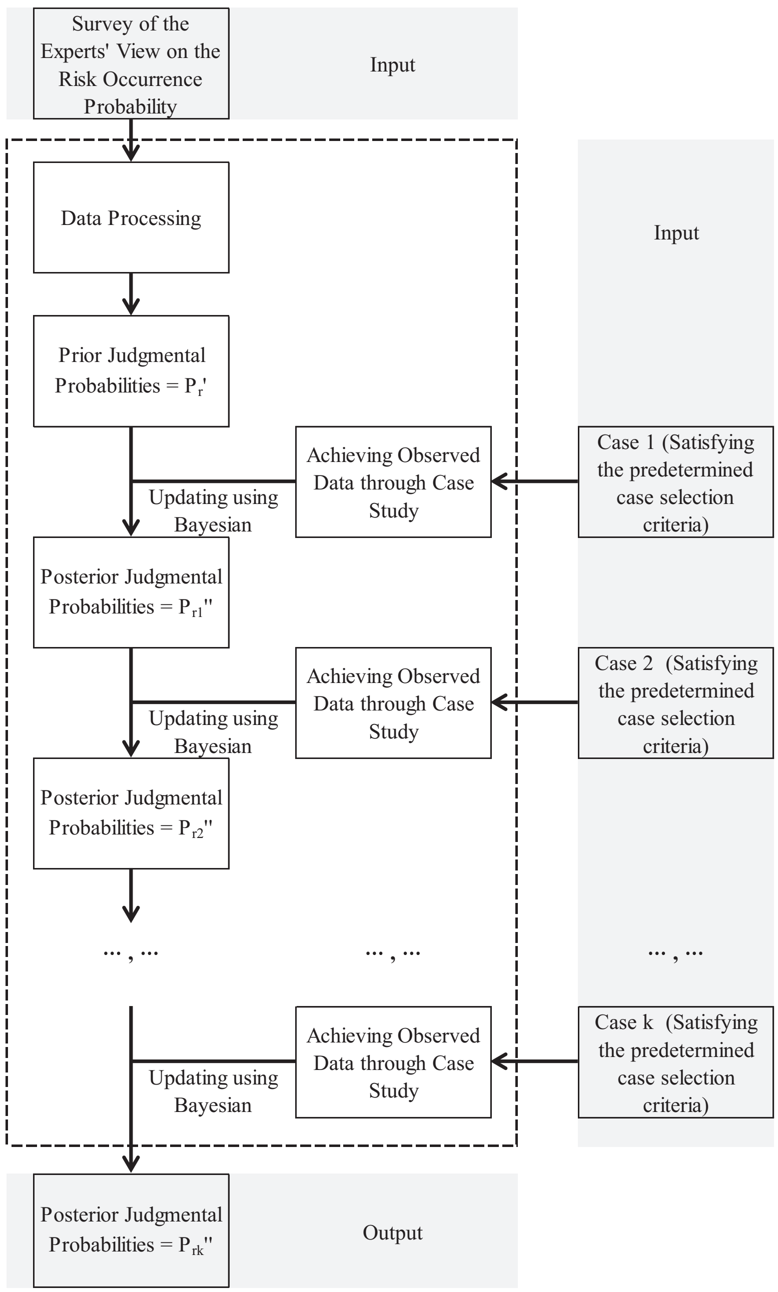

Fig. 3. Multiupdating procedures in the developed ROPFM-B approach.

factor; NP = total number of the valid respondents; and m = number of the estimated mean values of the occurrence probability given as the choices in the questionnaire.

In Eq. (2), the frequency of θ_j selected by the respondents for the risk factor is used as an approximate estimation of the chance, where θ_j = mean value of the risk occurrence probability based on the experts' judgments. The larger the sample size of the respondents, the better is the stability of using the frequency to estimate the probability (Bolstad and Curran 2016). For instance, if 30% of the surveyed experts indicated that the risk occurrence probability is around 0.5, then the prior probability at a risk occurrence level $\theta_j = 0.5$ should be calculated to be 0.3. In practice, a sample size of above 60 can be considered acceptable when using the frequency to be approximate to the probability (Bolstad and Curran 2016). The priori probability P'_r for the risk factor based on experts' judgments can be calculated through Eq. (3)

$$P'_r = \sum_{j=1}^{m} \theta_j \times P'_r(\theta_j), \quad 0 \le \theta_j \le 1; \quad j = 1, 2, \ldots, m \tag{3}$$

where P'_r = prior probability for the risk occurrence; $P'_r(\theta_j)$ = prior probability on the mean value of θ_j for the risk occurrence; θ_j = jth estimated mean value of the occurrence probability given as the choices for the risk factor in the questionnaire survey; and m = number of the estimated mean values of the occurrence probability given as the choices.

Step 3: Modeling Posterior Probability

The occurrence probability of the risk factor based on experts' judgments and the observed data through case study can be defined as the posterior probability in the ROPFM-B. It is denoted as P''_r, which is the posterior knowledge on the risk occurrence probability. When P'_r is achieved through Eq. (3), the next step of ROPFM-B is to update P'_r by integrating the risk-related data from real cases and get P''_r.

The status of actual risk events can be identified through the analysis of the selected cases or the statistic historical data recorded by the government or research institutions. Let ε_r represent that the risk happened in a case, and let ε_{-r} represent that the risk did not happen in a case. Later, the posterior probability distribution for the risk based on the experts' judgments and observed data through the case study could be achieved through Eq. (4). Finally, the risk occurrence probability P''_r, with all the risk ranges merged, can be calculated using Eq. (5)

$$P''_r(\theta_j) = \begin{cases} \dfrac{P(\varepsilon_r|\theta_j) \times P'_r(\theta_j)}{\sum_{j=1}^{m} P(\varepsilon_r|\theta_j) \times P'_r(\theta_j)} & \text{if } \varepsilon_r \text{ is observed} \\[2ex] \dfrac{P(\varepsilon_{-r}|\theta_j) \times [1 - P'_r(\theta_j)]}{\sum_{j=1}^{m} P(\varepsilon_{-r}|\theta_j) \times [1 - P'_r(\theta_j)]} & \text{if } \varepsilon_{-r} \text{ is observed} \end{cases}$$
$$0 \le \theta_j \le 1; \quad j = 1, 2, \ldots, m \tag{4}$$

$$P''_r = \sum_{j=1}^{m} \theta_j \times P''_r(\theta_j), \quad 0 \le \theta_j \le 1; \quad j = 1, 2, \ldots, m \tag{5}$$

where P''_r = posterior probability for the risk occurrence; $P''_r(\theta_j)$ = posterior probability on the mean value of θ_j for the risk

Table 1. Selected 22 PPP WTE incineration projects in China

Number	Projects	Province	Investment (million RMB)	MSW treatment capacity (t/day)
C_1	Beijing Liulitun	Beijing	800	2,000
C_2	Tianjin Shuanggang	Tianjin	578	1,200
C_3	Shandong Heze	Shandong	160	600
C_4	Shandong Zaozhuang	Shandong	290	1,000
C_5	Jiangsu Wujiang	Jiangsu	320	700
C_6	Ningbo Fenglin	Zhejiang	400	1,000
C_7	Shenzhen Pinghu	Guangdong	286	700
C_8	Shenzhen Nanshan	Guangdong	390	800
C_9	Shenzhen Yantian	Guangdong	200	450
C_{10}	Guangzhou Panyu	Guangdong	990	2,000
C_{11}	Guangzhou Likeng	Guangdong	722	1,000
C_{12}	Zhongshan Zhongxinzutuan	Guangdong	390	1,050
C_{13}	Zhengzhou Xingjin	Henan	245	1,000
C_{14}	Xuchang Tianjian	Henan	110	540
C_{15}	Wuhan Hankoubei	Hubei	530	2,000
C_{16}	Anhui Wuhu	Anhui	220	600
C_{17}	Chongqing Tongxin	Chongqing	315	1,200
C_{18}	Kunming Wuhua	Yunnan	322	1,000
C_{19}	Guangdong Huizhou	Guangdong	290	800
C_{20}	Shijiazhuang Qili	Hebei	160	500
C_{21}	Shanghai Jiangqiao	Shanghai	880	1,500
C_{22}	Shanghai Yuqiao	Shanghai	630	1,200

Note: RMB = renminbi.

occurrence; θ_j = jth estimated mean value of the risk occurrence probability given as the choice in the questionnaire survey; $P(\varepsilon_r|\theta_j)$ = probability of ε_r happening at the given probability of θ_j; $P(\varepsilon_{-r}|\theta_j)$ = probability of ε_{-r} happening at the given probability of θ_j; and m = number of the estimated mean values of the probability given as the choices.

Step 4: Multiupdating and Analytics

Generally, the larger the sample size of experts and cases, the more accurate is the estimation of the risk occurrence probability. If more cases are available and satisfying, then the predetermined case selection criteria (a multiupdating process) can be implemented. Fig. 3 illustrates the framework of the multiupdating process in the developed ROPFM-B approach. Here, P''_{rk} is the posterior probability for the risk after updating by k cases in total.

Typically, the estimated risk occurrence probability will be more accurate if more cases are available. However, there are no particular requirements on the sample size of cases in using Bayesian updating. As stated by Ang and Tang (2007), even if there are only one or two samples, the Bayesian updating remains meaningful because various sources and types of information are combined. This should be better than an estimation only based roughly on experts' judgments or historical data. In this study, 22 cases and 84 experts are involved in the application of the developed ROPFM-B approach to forecast the risk occurrence probability in PPP WTE incineration projects, which will be presented later in this research.

Risk Analysis in PPP Projects

PPP WTE Incineration Projects

With rapid economic growth and massive urbanization, the quantity of MSW has grown tremendously in the world since the 1980s

Table 2. Status description of revenue risk of the selected 22 PPP WTE incineration projects

Number	Risk happened or not	Event leading to revenue risk
C_1	No	Not applicable
C_2	Yes	The government did not fulfill its obligation of minimum revenue guarantee and pay the subsidy timely as promised, which caused a serious revenue risk of the project
C_3	Yes	The operation was suspended often by frequent reparation and maintenance due to the immature technical solution, which consequently caused revenue risk and serious financial loss
C_4	Yes	The government did not fulfill its obligation of providing the MSW treatment subsidy to the project, which caused the revenue risk
C_5	No	Not applicable
C_6	Yes	The quality and quantity of MSW supply did not achieve the standards as defined in the concession agreement, which caused revenue risk of the project
C_7	No	Not applicable
C_8	Yes	Because of the administration approval delay, the payment of the MSW treatment and power generation was deferred, causing financial loss to the private sector
C_9	Yes	The design capacity of the project was 450 t/day; however, the MSW supply was only 200 t/day, which caused revenue risk to the project; also, because of the administration approval delay, the payment of MSW treatment and power generation was deferred, causing financial loss to the private sector
C_{10}	Yes	The boiler was always blocking up because of construction waste and large pieces of metal; 10 operation incidents happened in 4 months since the project entered into operation phase due to the low quality of MSW; consequently, the revenue was much less than expected
C_{11}	Yes	Because the MSW supply could not achieve the design capacity, the private sector had to stop operating parts of the machines, which caused revenue risk to the project
C_{12}	No	Not applicable
C_{13}	No	Not applicable
C_{14}	Yes	The price of the power generation was even lower than the coal-fired power station, and the price of electricity used in this project was at the industrial power level and could not be deducted by the power generation because there was no complete law before 2012 to guarantee the project would get the approval of the renewable power price policy on time, causing financial loss
C_{15}	Yes	Because of the insufficient MSW supply, the electricity generated was even not enough for auxiliary power and caused serious revenue risk, and the payment for MSW treatment was deferred by the local government, causing financial loss to the project
C_{16}	Yes	The main technology used in this project was imported from the US, which was not suitable to the properties of local MSW; the approval of the MSW treatment tariff and power general price was delayed, which caused revenue risk to the project; because of the public's unwillingness to pay for the MSW treatment, the local government did not have enough money to pay for the project on time as promised
C_{17}	No	Not applicable
C_{18}	No	Not applicable
C_{19}	No	Not applicable
C_{20}	No	Not applicable
C_{21}	Yes	The boiler was always blocking up because of construction waste and large pieces of metal; 10 operation incidents happened in 4 months since the project entered into the operation phase due to the low quality of MSW; consequently, the revenue was much less than expected
C_{22}	Yes	Because the MSW supply could not achieve the design capacity, the private sector had to stop operating parts of the machines, which caused revenue risk to the project

(Song et al. 2013). The huge storage of MSW disposal shows a great need for developing alternative solutions in the entire world. According to the statistical reports, China recently surpassed the US as the largest MSW producer (Cointreau 2007) and is associated with the annual generation of more than 150 million tons of MSW and an annual increasing rate of 8–10% (Asian Development Bank 2010). It is predicted that, in China, the annual MSW generation will increase to at least 480 million tons by 2030 (Hoornweg et al. 2005). As a renewable source of energy, WTE incineration is playing an increasingly important role in MSW management and has been widely applied in many developed and developing countries. The original MSW volume can be reduced by 90% or even 95% through WTE incineration plants if modern incinerators are adopted (Ham and Lee 2017).

The development of WTE incineration plants requires large-scale investment, which is a big challenge to various levels of governments. PPP is regarded as an effective mechanism to attract investment from the private sector and to improve efficiency in providing infrastructure and public services, especially in emerging markets (Farquharson et al. 2011). Actually, many WTE incineration projects have been developed through PPP arrangements (Chen et al. 2010); for instance, more than 70% of the WTE incineration projects have been developed through PPP in China (Song et al. 2013). However, due to the large construction cost, technical difficulties, and the long concession period associated with PPP arrangements, many serious risk events or even failures have taken place in PPP WTE incineration projects. Therefore, it is helpful to give a more reasonable estimation on risk occurrence probability so that the stakeholders could allocate the limit time and resources on significant risks and manage them more effectively.

Identification of Critical Risk Factors

Regarding PPP WTE incineration projects, revenue issues (Song et al. 2013), environmental problems (Chen and Lin 2008; Mills et al. 2006), and technological shortcomings (Ménard et al. 2006) are the three most important issues. For instance, redundant coal usage for MSW incinerating may worsen regional environments (Asian Development Bank 2007). Poor operational efficiency and low technological levels are severe obstacles to the project's success (Asian Development Bank 2009). Wang and Zhang (2017) identified 21 critical risk factors for PPP WTE incineration projects. Based on the factor analysis, seven components were extracted from all 21 risk factors. For example, risk factors of government credit risk, government decision-making risk, revenue risk, land acquisition and administration approval risk, and incompleteness of law or change in law are grouped into the same group because such risk factors always happen due to the lack of government support (Wang and Zhang 2017). In this research, seven risk factors were selected from each group classified by Wang and Zhang (2017) to investigate the risk occurrence probability using ROPFM-B. These seven risks are (1) revenue risk, (2) interest rate risk, (3) private sector credit risk, (4) construction cost overrun, (5) operational performance risk, (6) environmental pollution, and (7) technical risk.

The local government subsidy for MSW treatment and the revenue of the generated power sold to the grid are the main cash inflows of PPP WTE incineration projects. These cash inflows are used to repay loans, recover the initial cost, and receive reasonable profits (Song et al. 2013). Sometimes the MSW separation and revenue from recycling before incineration can bring additional cash inflows to the project. The revenue risk in a PPP WTE incineration project indicates that the revenue from MSW treatment and power generation is much less than expected. Song et al. (2013) indicated that the revenue is a critical risk in PPP WTE incineration projects because a serious revenue risk would lead to financial loss of the project and even cause private sector default. In this study, we are going to use the revenue risk as an example to show the computation procedures of the developed ROPFM-B approach.

Case Study

Background

In this research, 22 PPP WTE incineration projects were identified in China and coded as C_1–C_{22}. Table 1 provides detailed information of these projects, such as project name, investment, waste treatment capacity, government subsidy, and the current status. The revenue risk of each project was carefully examined and summarized in Table 2. For example, in the Tianjin Shuanggang project (C_2), the government did not fulfill its obligation of a timely minimum revenue guarantee and pay subsidy as promised, which caused a serious revenue risk to the project.

Table 3. Statistical analysis of the returned 84 respondents

Category	Number of respondents	Percentage
1. Based on organization type		
(1) Research institute	17	20.2
(2) Government	8	9.5
(3) Investor	31	36.9
(4) Consultant/legal adviser	5	6.0
(5) Lender (e.g., bank)	23	27.4
2. Based on research/working experience in PPPs		
(1) Less than 2 years	13	15.4
(2) 2–4 years	46	54.8
(3) 5–10 years	21	25
(4) 11–15 years	2	2.4
(5) More than 15 years	2	2.4
3. Based on working experience in PPP practice		
(1) 1 or 2 projects	19	22.6
(2) 3–5 projects	32	38.1
(3) 6–10 projects	17	20.2
(4) 11–20 projects	10	11.9
(5) More than 20 projects	6	7.2
4. Based on working experience in PPP WTE incineration practice		
(1) 1 or 2 projects	58	69
(2) 3–5 projects	25	29.8
(3) 6–10 projects	1	1.2
(4) 11–20 projects	0	0
(5) More than 20 projects	0	0

Table 4. Experts' judgments on the mean value of the revenue risk occurrence probability in PPP WTE incineration projects

Mean value (θ)	Number of respondents
0.1	10
0.3	30
0.5	29
0.7	12
0.9	3

Data Resources

A questionnaire survey was conducted to solicit expert opinions on the risk occurrence probability for PPP WTE incineration projects.

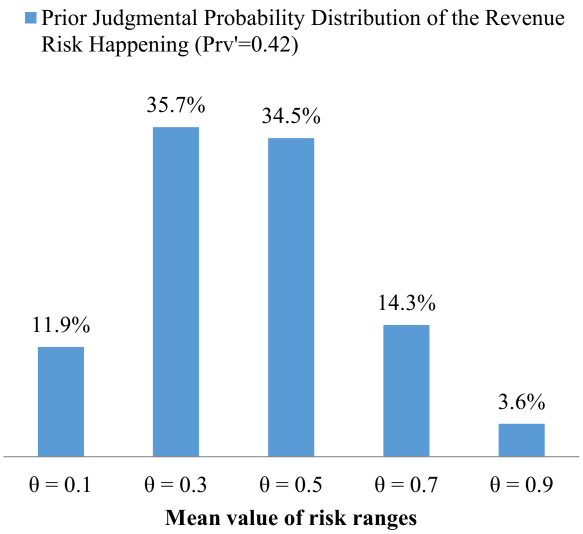

Fig. 4. Prior judgmental probability distribution of the revenue risk happening in PPP WTE incineration projects.

In this study, a newly developed database by the National Development and Reform Commission (NDRC) in China, which consists of 343 certified experts in the PPP domain, is used to identify survey respondents. Around 160 questionnaires were sent out to the expert database through emails, and 84 respondents returned back with complete questionnaires. All respondents had research or working experience in PPP WTE incineration projects in China. Among the returned respondents, 67 came from the industry and 17 came from the academia. Table 3 illustrates statistical analysis details on the returned 84 respondents. As shown clearly in Table 3, 84.6% of the surveyed experts have at least 2 years of research/working experience in PPPs, and 77.4% of the surveyed experts have undertaken at least three PPP projects in actual practice. Generally, the majority of the respondents are quite familiar with the PPP practice, increasing the quality of the questionnaire data and the persuasiveness of the analysis results to a large extent.

In the questionnaire, the present estimated mean values (θ) of the risk occurrence probability are provided as the choices, which are "$\theta = 0.1$, $\theta = 0.3$, $\theta = 0.5$, $\theta = 0.7$, and $\theta = 0.9$." Table 4 illustrates experts' judgments on the mean value of the revenue risk occurrence probability in PPP WTE incineration projects. It is clear that 10 experts agreed that the mean value of the revenue risk occurrence probability was close to 0.1.

The prior judgmental probability distribution of the revenue risk is calculated using Eq. (1), and the raw data needed is shown in Table 4. Fig. 4 gives the prior judgmental probability distribution of the revenue risk. By using Eq. (2), the prior judgmental probability

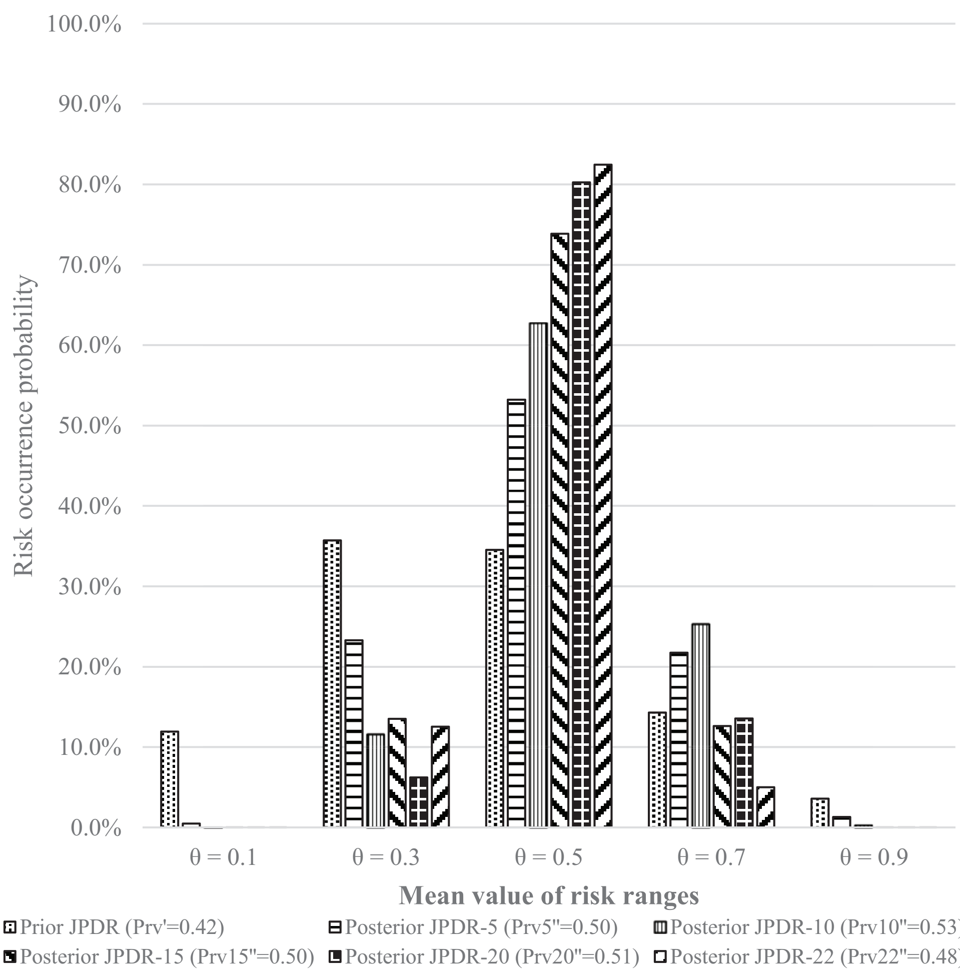

Fig. 5. Updating process of the posterior probability distribution of the revenue risk occurrence by integrating the observed data through cases.

of the revenue risk occurrence (P'_{rv}) in a PPP WTE incineration project is calculated to be

$$\frac{0.1 \times 10 + 0.3 \times 0 + 0.5 \times 29 + 0.7 \times 12 + 0.9 \times 3}{84} = 0.42$$

Probability Updating

Table 2 describes the status of the revenue risk encountered in the 22 projects. The data needed to calculate the posterior probability can be obtained from Eq. (4). For example, as shown in Table 2, ε_{-rv1} means the revenue risk not happened is observed in C_1, ε_{rv2} means the revenue risk happened is observed in C_2, and ε_{rv3} means the revenue risk happened is observed in C_3.

The revenue risk-related data observed from the 22 projects (Table 2) is used to update P'_{rv} using Eq. (5) to calculate the posterior probability of revenue risk occurrence. The results of the continuous updating process are shown in Fig. 5, which shows that the posterior probability distribution is changing when integrating with more historical cases in a dynamic manner.

In Fig. 5, the Prior JPDR = prior probability distribution of revenue risk, Posterior JPDR-5 = posterior probability distribution of the revenue risk occurrence after integrating the data from 5 cases, Posterior JPDR-10 = posterior probability distribution of the revenue risk occurrence after integrating the data from 10 cases, Posterior JPDR-15 = posterior probability distribution of the revenue risk occurrence after integrating the data from 15 cases, Posterior JPDR-20 = posterior probability distribution of the revenue risk occurrence after integrating the data from 20 cases, and Posterior JPDR-22 = posterior probability distribution of the revenue risk occurrence after integrating the data from 22 cases.

Comparison Analysis

After integrating data from the selected 22 cases, it is found that, by using the developed ROPFM-B approach, the final estimated revenue risk occurrence probability for PPP WTE incineration projects in China is calculated to be 0.48. It is a little higher than the experts' judgments ($P'_{rv} = 0.42$). Fig. 6 illustrates the comparison of the prior and posterior probability distribution of the revenue risk occurrence in PPP WTE incineration projects.

Generally, the risk occurrence probability can be forecast based on the historical data if the sample is big enough to give a solid estimation. However, there are no big databases recording the risk occurrence status in PPP WTE incineration projects in China. Thus, it is difficult to give a sound estimation of the risk occurrence probability based on the historical data. As shown in Fig. 7, in this study, we have recorded 22 historical cases of the revenue risk events. Based on the entire sample of the 22 cases, the probability of revenue risk occurrence should be 0.5. If there are only four cases available in practice, then the probability of the revenue risk occurrence is 0.75 based on the data of the first, second, third, and fourth cases, which is much higher than the revenue risk occurrence probability (0.5) based on the entire sample (22 cases). However, the forecasting result using ROPFM-B is 0.56, in which the experts' judgments and the data from the four cases are considered. As a conclusion, it is easy to find out that a better estimation by using the ROPFM-B can be achieved when the historical data are limited.

Discussions

The final estimated occurrence probabilities of the identified seven critical risk factors are shown in Table 5. Based on the experts'

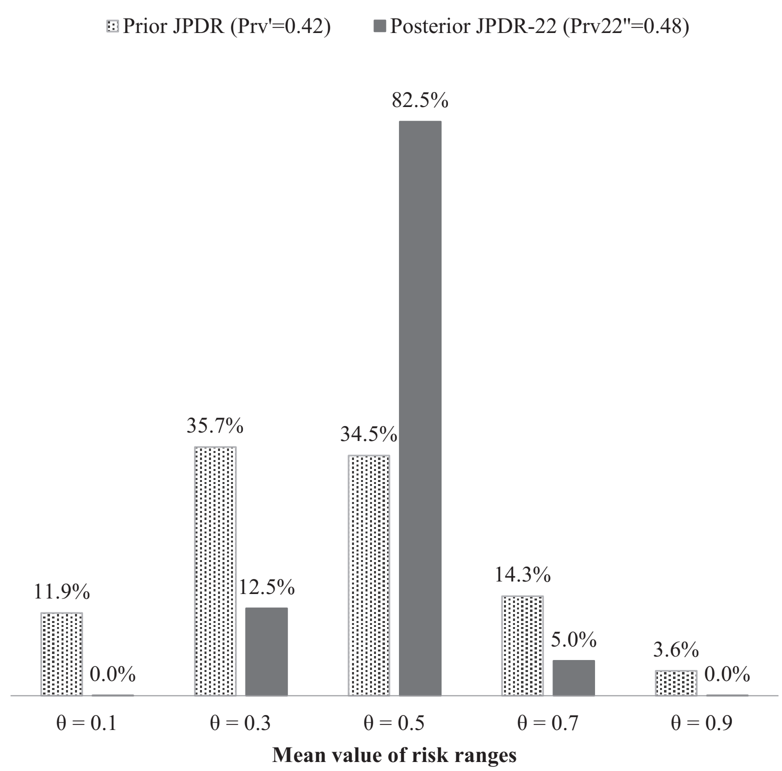

Fig. 6. Comparison of prior probability distribution and posterior probability distribution of the revenue risk occurrence in PPP WTE incineration projects.

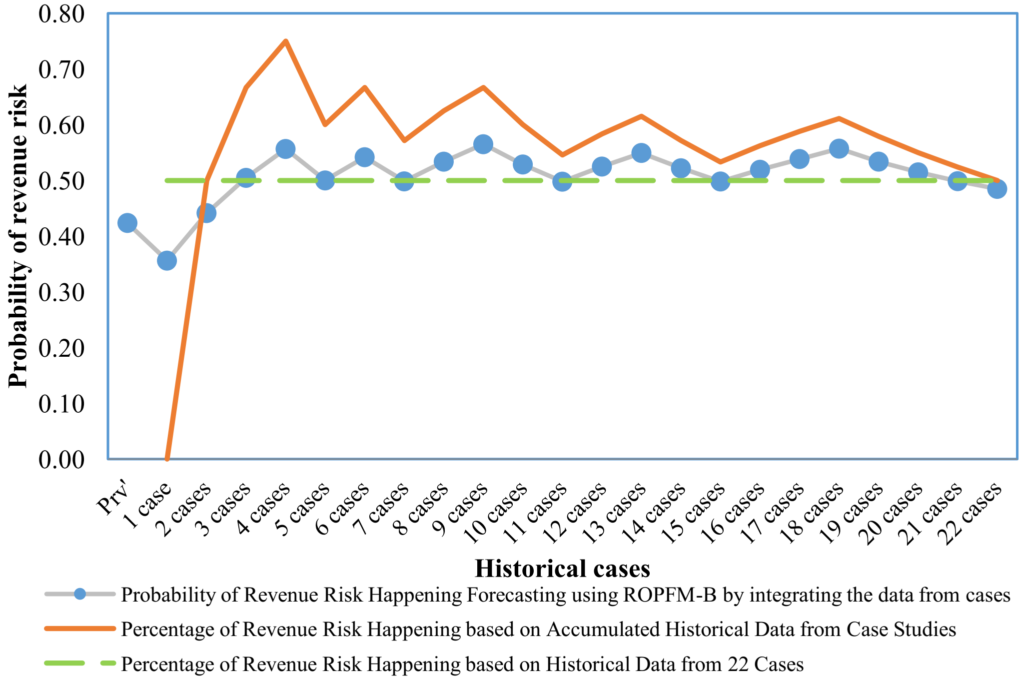

Fig. 7. Posterior probability of revenue risk occurrence using ROPFM-B and percentage of revenue risk occurrence based on case studies.

experiences, the construction cost overrun is considered as easily encountered in PPP projects. However, after integrating the risk-related data from real cases using ROPFM-B, the final estimated occurrence probabilities (posterior probabilities) of the environmental risk and revenue risk are much higher than the experts' judgments (prior probabilities).

The upper and lower control lines could help investigate differences between prior and posterior probabilities. In this research, the upper and lower control lines are simply 20% larger and smaller than the prior probability, respectively. Fig. 8 illustrates a comparison of the prior and posterior probability for seven critical risk factors using ROPFM-B for PPP WTE incineration projects. It is clear that there are four risk factors that have significant differences in prior and posterior probability including construction cost overrun, operational performance risk, private sector credit risk, and environmental pollution.

According to the outputs of ROPFM-B, the final estimated occurrence probabilities for the risk factors of construction cost overrun, operational performance risk, and private sector credit risk are lower than the experts' expectations. For the risk factor of construction cost overrun, the risk occurrence probability based on expert's judgments is 0.50, whereas the final result by using ROPFM-B is 0.11. Generally, this is because construction cost overrun is one of the critical risk factors in the construction project and is always encountered in practice.

Overall, based on the analysis of revenue risk occurrence probability forecasting using ROPFM-B, it is found that ROPFM-B can help decision makers comprehensively estimate the risk occurrence probability and give a better estimation when historical cases are available. The model will be helpful in risk prioritization because the criteria included in risk prioritization and assessment are the chance of risk occurrence and the loss caused by the risk (Dikmen et al. 2012; Li and Zou 2011). After achieving a sound risk occurrence probability forecast, the stakeholders could later allocate the limit time and resources on significant risks and manage them more effectively.

Table 5. Final occurrence probabilities of seven critical risk factors for PPP WTE incineration projects

Number	Risk factor	Prior judgmental probability	Posterior judgmental probability
1	Revenue risk	0.42	0.48
2	Interest rate risk	0.35	0.33
3	Private sector credit risk	0.36	0.13
4	Construction cost overrun	0.50	0.11
5	Operational performance risk	0.44	0.32
6	Environmental pollution	0.30	0.51
7	Technical risk	0.25	0.31

Conclusions and Future Works

In this research, an improved methodology of forecasting risk occurrence probability, ROPFM-B, has been developed based on the Bayesian updating approach. Data resources required as inputs come from two aspects: (1) experts' judgments on the risk occurrence probability and (2) historical records about risk events in real cases. The experts' judgments collected via questionnaire surveys or interviews are used to model prior probabilities. The observed historical cases are used to continuously update the experts' prior estimation by using the Bayesian theorem approach to achieve a more accurate estimation of the risk probability in PPP projects for more targeted solutions in risk response and allocation. The developed methodology is capable of limiting the subjectivity of experts' judgments through the continuous updating of prior estimation with the observed real data. With the expert's subjective judgments compared, a better estimation of risk probability can be reached, even when the observed historical cases are limited.

The ROPFM-B is applied to forecasting the risk occurrence probability for PPP WTE incineration projects, in which 22 cases and 84 experts are involved as inputs. Seven critical risk factors

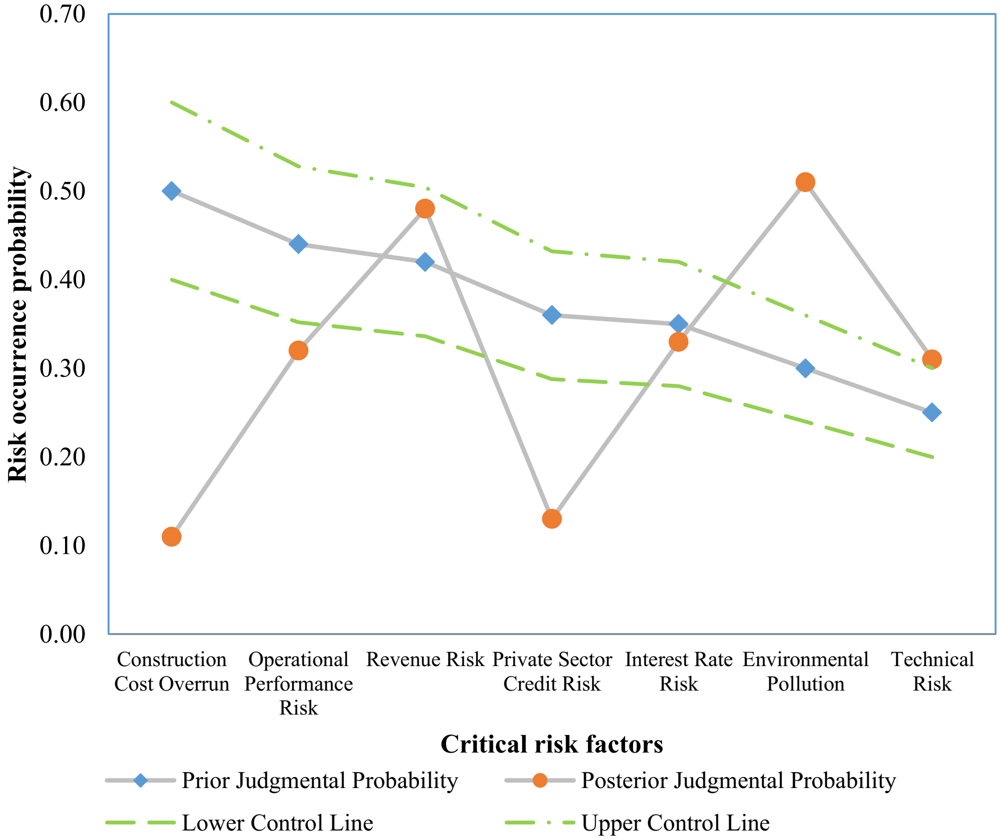

Fig. 8. Comparison of prior and posterior probability of risk occurrence using ROPFM-B for PPP WTE incineration projects.

have been selected: (1) revenue risk, (2) interest rate risk, (3) private sector credit risk, (4) construction cost overrun, (5) operational performance risk, (6) environmental pollution, and (7) technical risk. The questionnaire survey and case study are used to collect data as inputs from ROPFM-B. Through the continuous updates in ROPFM-B, there are four risk factors, including construction cost overrun, operational performance risk, private sector credit risk, and environmental pollution, which have significant differences between prior and posterior probabilities. The construction cost overrun is considered as easily encountered based on experts' judgments. However, after integrating the risk-related data from real cases, it is found that the environmental risk and revenue risk always happened in practice. The finally estimated occurrence probabilities of these risk factors are much higher than experts' judgments. Much more attention should be paid to mitigate those risks for a better delivery of PPP WTE incineration projects.

The developed approach also has some limitations for further studies. In this research, the observed status of risks in real cases is defined as a binary event, namely, (1) the risk event occurs and (2) the risk event does not occur. The severity of the occurring risk event is not subdivided. For instance, the revenue risk is defined as the overrated revenue. The revenue risk occurs when the actual revenue is less than expected. However, for the actual revenue, 90% of the expected revenue should be much different with 60% of the expected revenue. In other words, the measurement of risk magnitude in real cases is a fuzzy problem. Our subsequent research will focus on exploring the fuzzy nature in the measurement of risk magnitude and investigating the impact of multistate real events on the continuous update in the estimation of risk probability. More advanced methods in combination with the Bayesian technique, such as Monte Carlo simulations, will be proposed to incorporate more data inputs to largely reduce the uncertainty and improve the accuracy of model prediction.

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