Example-dependent cost-sensitive learning for public- private partnership contract failure prediction

Wang, Yongqi

2021

Wang, Y. (2021). Example-dependent cost-sensitive learning for public- private partnership contract failure prediction. Doctoral thesis, Nanyang Technological University, Singapore.
<https://hdl.handle.net/10356/154522>

<https://hdl.handle.net/10356/154522>

<https://doi.org/10.32657/10356/154522>

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EXAMPLE-DEPENDENT COST-SENSITIVE LEARNING FOR PUBLIC-PRIVATE PARTNERSHIP CONTRACT FAILURE PREDICTION

WANG YONGQI
SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING
2021

**EXAMPLE-DEPENDENT COST-SENSITIVE LEARNING FOR PUBLIC-
PRIVATE PARTNERSHIP CONTRACT FAILURE PREDICTION**

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School of Civil and Environmental Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

2021

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Tiong Lee Kong, Robert

Authorship Attribution Statement

This thesis contains material from five papers that were published/submitted in the following peer-reviewed journals in which I am listed as an author.

1. Chapter 4 is published as Wang Yongqi, Zengqi Xiao, Robert Tiong, and Zhang Limao. “Data-driven quantification of public-private partnership experience levels under uncertainty with Bayesian hierarchical model.” *Applied Soft Computing* 103 (2021): 107176. <https://doi.org/10.1016/j.asoc.2021.107176>.

The contributions of the co-authors are as follows:

- I wrote the manuscript drafts. The manuscript was reviewed by Assistant Professor Zhang Limao, Associate Professor Robert Tiong, and Dr. Xiao Zengqi.
- I collected the database from the World Bank website and conducted the data cleaning and preprocessing.
- I proposed the hybrid Bayesian hierarchical model to analyze the raw data to quantify countries’ PPP experience levels.

2. Chapter 5 is published as Wang Yongqi, Vimal Kumar Thangasamy, Zhaoqi Hou, Robert Tiong, and Limao Zhang. “Collaborative relationship discovery in BIM project delivery: A social network analysis approach.” *Automation in Construction* 114 (2020): 103147. <https://doi.org/10.1016/j.autcon.2020.103147>.

The contributions of the co-authors are as follows:

- I wrote the manuscript drafts. The manuscript was revised by Assistant Professor Zhang Limao and Associate Professor Robert Tiong.
- I co-designed the study with Zhaoqi Hou and A/Prof Robert Tiong, as well as conducted the survey with Zhaoqi Hou and Vimal Kumar Thangasamy. I have also analyzed the initial raw data.
- I proposed the research method based on the Social Network Analysis approach to analyze the collaborative relationships between different

stakeholders in a BIM project. This method has been adopted in this research to find the relationships between different countries in transferring PPP knowledge.

3. Chapter 5 is submitted as Wang Yongqi, and Robert Tiong. “Evolution of knowledge transfer in public-private partnership projects: A global perspective.” *Engineering Construction and Architectural Management* (2021).

The contributions of the co-authors are as follows:

- I wrote the manuscript drafts. The manuscript was revised by A/Prof Robert Tiong.
 - I collected the data from the World Bank website and cleaned the data sets. I also analyzed and presented the data.
4. Chapter 6 is published as Wang Yongqi, Shao Zhe, and Robert Tiong. “Data-driven prediction of contract failure of public-private partnership projects.” *ASCE Journal of Construction Engineering & Management* 147 (2021). [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0002124](https://doi.org/10.1061/(ASCE)CO.1943-7862.0002124).

The contributions of the co-authors are as follows:

- A/Prof Robert Tiong and Dr. Shao Zhe suggested the research direction.
 - I wrote the manuscript drafts. The manuscript was revised by Associate Professor Robert Tiong.
 - I collected the data from the World Bank website and cleaned the data sets. I also analyzed and presented the data.
5. Chapter 7 is published as Wang Yongqi, and Robert Tiong. “Public-private partnership contract failure prediction using example-dependent cost-sensitive models.” *ASCE Journal of Management in Engineering* 38 (2021). [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000990](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000990)

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ACKNOWLEDGEMENTS

The author would like to express his most sincere appreciation and gratitude to his supervisor Associate Professor Tiong Lee Kong, Robert for his continuous support and guidance during the period of study at Nanyang Technological University (NTU), Singapore. His kindness and encouragement have motivated me along with the smooth progress of the thesis. The author has learned how to carry out research independently, and most importantly, how to be a responsible and kind person from his supervisor.

The author would also like to thank his TAC members, Associate Professor Qian Shunzhi and Assistant Professor Zhang Limao, for their valuable and useful suggestions. Their rigorous attitude towards the research would have a profound influence on the author's life and work.

Special thanks to the author's friends, Dr. Shao Zhe, Dr. Aaron Sham, and Dr. Wang Longqi, for their advice, suggestions, and assistance on the thesis. Also, special thanks to the author's classmates, Li Shuai, Lan Xiaoyi, Zhu Gaoming, and Zhong Yukai, for their goodness to accompany the author. This friendship has made the Ph.D. life more interesting and meaningful.

The author also would like to express special thanks to the School of CEE of Nanyang Technological University, Singapore for providing a good research environment.

Especially, the author would like to express his sincere thanks to his parents for their bringing up of me and their dedication and support.

Finally, the author would like to thank his girlfriend Yang Yang, who has given unconditional support for almost every decision that he has ever made. The author appreciates her valuable support and suggestions for each crucial point in his life, especially in Singapore. Thanks for her persistence and accompany in the past 6 years since knowing her.

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SUMMARY

The public-private partnership (PPP) mode of procurement is increasingly encouraged by governments to deliver public infrastructure and services in developing countries. However, PPP projects have a high risk of encountering a contract failure due to their complex characteristics. Failure of a PPP contract can bring considerable impacts to both the public and private sectors. For example, the public agencies may undergo a heavy financial burden by redeeming the private share, and the private sponsors may receive a bad reputation. Despite various factors determining the final status of a PPP project have been found, some potential determinants, such as countries' PPP experience and importance in transferring PPP knowledge, have been overlooked. Besides, very few studies have attempted to predict the outcome of a PPP project using project-specific and country-specific factors from a quantitative standpoint. This research is thus carried out to accomplish the following objectives and outcomes.

First, a data-driven approach is used to quantify countries' PPP experience levels through the hybrid Bayesian hierarchical model with uncertainties considered. Detailed data exploration and selection are carried out to clean the data source, followed by the change point detection using the hybrid Bayesian hierarchical model. As a result, different experience levels for one hundred and seventeen developing countries are obtained based on the location of the change points. Four experience levels are suggested for the energy sector, while five levels are found for the transportation and water & sewerage (W&S) sectors. The outcomes can help investors choose the right investment directions.

Second, the social network analysis (SNA) technique is used to evaluate the evolution of the PPP knowledge transfer around the world. The importance of both developing and developed countries in transferring the PPP knowledge is represented using the SNA metrics, such as out-degree centrality, in-degree centrality, and the PageRank. The results show that though the importance of a country in transmitting PPP knowledge is changing with time, some are always at key positions. The outcomes provide a guideline on selecting appropriate PPP partners to achieve performance improvement.

Finally, to proactively predict the PPP contract failure, an example-dependent cost-sensitive machine learning (ECS-ML) model is proposed in the context of the PPP domain. The conventional machine learning models are first used to obtain the most significant failure factors from a quantitative perspective. Moreover, the ECS-ML model is used to predict PPP contract failure by optimizing the total cost of misclassifications. The opportunity cost and equity loss are treated as the potential cost of misclassifying a successful and failed project, respectively. The performance of the model is evaluated using the profit-oriented and the accuracy-oriented metrics, such as the cost-saving and F_1 score. The results highlight that the most precise models are not necessarily the most cost-effective. Besides, the effectiveness of the previously proposed indicators, including countries' experience levels and importance in transferring PPP knowledge, are also verified.

LIST OF PUBLICATIONS

1. Wang Yongqi, Robert Tiong, and Zhang Limao. “Data-driven quantification of public-private partnership experience levels under uncertainty with Bayesian hierarchical model.” *Applied Soft Computing* 103 (2021): 107176. <https://doi.org/10.1016/j.asoc.2021.107176>. Corresponding to Chapter 4.
2. Wang, Yongqi, Vimal Kumar Thangasamy, Zhaoqi Hou, Robert LK Tiong, and Limao Zhang. “Collaborative relationship discovery in BIM project delivery: A social network analysis approach.” *Automation in Construction* 114 (2020): 103147. <https://doi.org/10.1016/j.autcon.2020.103147>. Corresponding to Chapter 5.
3. Wang Yongqi, and Robert Tiong. “Evolution of knowledge transfer in public-private partnership projects: A global perspective.” *Engineering Construction and Architectural Management* (submitted on March 2021). Corresponding to Chapter 5.
4. Wang Yongqi, Shao Zhe, and Robert Tiong. “Data-driven prediction of contract failure of public-private partnership projects.” *ASCE Journal of Construction Engineering & Management* 147 (2021). [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0002124](https://doi.org/10.1061/(ASCE)CO.1943-7862.0002124). Corresponding to Chapter 6.
5. Wang Yongqi, and Robert Tiong. “Public-private partnership contract failure prediction using example-dependent cost-sensitive models.” *ASCE Journal of Management in Engineering* 38 (2021). [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000990](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000990). Corresponding to Chapter 7.

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LIST OF ABBREVIATIONS

AD	Average Degree
ADASYN	Adaptive Synthetic
AI	Artificial Intelligence
ANN	Artificial Neural Network
AUC	Area Under the ROC Curve
AUPRC	The Area Under the PR Curve
BF	Build and Finance
BOO	Build-Own-Operate
BOOT	Build-Own-Operate-Transfer
BOT	Build-Operate-Transfer
BTO	Build-Transfer-Operate
CD	Degree Centrality
CPI	Consumer Price Index
CSF	Critical Success Factor
DBF	Design-Build-Finance
DBFO	Design-Build-Finance-Operate
DBFOM	Design-Build-Finance-Operate-Maintain
DCMF	Design-Construct-Manage-Finance
DPR	Dividend Payout Ratio
DSCR	Debt Service Coverage Ratio
DSU	Project Status Changed
EAP	East Asia and Pacific
ECA	Europe and Central Asia
ECS	Example-dependent Cost-sensitive
ECS-ML	Example-dependent Cost-sensitive Machine Learning
EPC	Engineering, Procurement, and Construction
FCY	Financial Closure Year
FDI	Foreign Direct Investment
FN	False Negative
FP	False Positive
FPR	False Positive Rate
GBDT	Gradient Boosting Decision Tree

GDP	Gross Domestic Product
HPD	Highest Posterior Density
ICT	Information and Communications Technology
ID	In-degree Centrality
IDA	International Development Association
IDB	Inter-American Development Bank
ISMED	Investment Security in the Mediterranean
KDE	Kernel Density Estimate
KNN	k-Nearest Neighbors
LAC	Latin America and Caribbean
LGB	LightGBM
LR	Logistic Regression
MCMC	Markov Chain Monte Carlo
MDBs	Multilateral Development Banks
MENA	Middle East and North Africa
ML	Machine Learning
MSW	Municipal Solid Waste
ND	Network Diameter
NLP	Natural Language Processing
OD	Out-degree Centrality
PC	Principal Component
PCA	Principal Component Analysis
PDF	Probability Density Function
PFI	Private Finance Initiative
PPI	Private Participation in Infrastructure
PPP	Public-Private Partnership
PPPLRC	Public-Private Partnership Legal Resource Center
PR	PageRank
QA	Quantitative Analysis
RF	Random Forest
ROC	Receiver Operating Characteristic
ROE	Return on Equity
ROT	Rehabilitate-Operate-Transfer

SA	South Asia
SIC	Schwarz Information Criterion
SMOTE	Synthetic Minority Oversampling Technique
SNA	Social Network Analysis
SPV	Special Purpose Vehicle
SSF	Sub-Saharan Africa
TN	True Negative
TP	True Positive
TPR	True Positive Rate
UD	Unweighted Density
WD	Weighted Density
WDI	World Development Indicators
WGI	Worldwide Governance Indicators
W&S	Water & Sewerage
XGB	XGBoost

LIST OF SYMBOLS

Symbol	Description	Location
δ	the threshold used to choose an active project	Chapter 3
m	the number of the change points	Chapter 4
n	the size of the data set	Chapter 4
τ_m	the position of the change point m	Chapter 4
y_τ	the change point	Chapter 4
r_j	the contract failure rate	Chapter 4
C	the cost function of each segment in the binary segmentation method	Chapter 4
β	the parameter in the penalty in the Schwarz Information Criterion	Chapter 4
p	the number of the additional parameters introduced by adding one more change point	Chapter 4
y	observables in a data set	Chapter 4
$p(\theta \varphi)$	the prior distribution of a Bayesian model	Chapter 4
$p(y \theta)$	the likelihood function of a Bayesian model	Chapter 4
$p(\varphi)$	the hyper-prior distribution of a Bayesian model	Chapter 4
n_j	the number of failed projects at experience j for all countries	Chapter 4
N_j	the sum of projects finished at experience j in different countries	Chapter 4
n_i	the i th node in a network	Chapter 5
ω_{ij}	the weight of the tie from node i to node j	Chapter 5
d	the damping factor in the PageRank	Chapter 5
x_n	the n th attribute in the data set	Chapter 6
PC_i	the i th principal component	Chapter 6
a_{in}	the loading of variable x_n for the PC_i	Chapter 6
t	the linear combination of independent variables of a data set	Chapter 6
b_n	the estimated coefficient from the data set	Chapter 6
$D_{Minkowski}(x,y)$	the Minkowski distance between two points x and y	Chapter 6
c_0	the predicted negative label	Chapter 7
c_1	the predicted positive label	Chapter 7

C_{TP}	the cost of correctly classifying a positive sample	Chapter 7
C_{TN}	the cost of correctly classifying a negative sample	Chapter 7
C_{FP}	the cost of misclassifying a negative sample	Chapter 7
C_{FN}	the cost of misclassifying a positive sample	Chapter 7
d_{ji}	the dividend of the project j in the year i	Chapter 7
NI_{ji}	the net income of the project j in the year i	Chapter 7
ROE_{ji}	the return on equity of the project j in the year i	Chapter 7
f_{s_j}	the success fee of the project j	Chapter 7
f_{a_j}	the arranging fee of the project j	Chapter 7
$L(y, t)$	the cross-entropy of one sample in a data set	Chapter 7
$C(Y, T)$	the average loss of all samples in a data set	Chapter 7
Y	the set of the true label of all samples in a data set	Chapter 7
T	the set of the predicted softmax probability of all samples in a data set	Chapter 7
f_0	the classifier that predicts all samples as the class c_0	Chapter 7
f_1	the classifier that predicts all samples as the class c_1	Chapter 7

Chapter 1 Introduction

1.1 Research Background

The significant role of infrastructures, such as airports, railroads, telecom, and seaports, played in economic growth and poverty alleviation has long been realized and acknowledged by governments around the world (Osei-Kyei and Chan 2019). In the early 1970s, these projects are generally financed by official sources, including the government, multilateral development institutions, and export promotion agencies of a country (Lee et al. 2018). However, governments are turning to private resources to build and operate public infrastructure to overcome the financial and technical deficit due to the high cost of public debts and increasing demand for these infrastructure facilities (Mohsin et al. 2011). Fig. 1.1 shows that the total real investment in the infrastructure with private participation has shown a rising trend in the developing economies since 1990.

Fig. 1.1. Investments in PPI projects, 1990-2019 (data source: PPI database)

There are different types of private involvement depending on the degree of transfer of asset ownership and management of the service, such as divestment and public-private partnership (PPP) (Calabrese 2008). PPP is broadly defined as “a long-term contract between a private party and a government entity, for providing a public asset or services, in which the private party bears significant risk and management responsibility, and remuneration is linked to performance” (World Bank 2017). It is increasingly being used as a common procurement way in various sectors, including highway and water treatment, because of the benefits such as improvement of service

quality, alleviation of public financial burden, and promotion of economy (Owolabi et al. 2020; Rohman and Wiguna 2019). PPP is one type of private involved project, and what makes it different from other procurement modes are the attributes of risk-sharing between public and private sectors, together with the long duration of the contract. It is easier to be adversely influenced by various risks, leading to the failure of projects (Sarvari et al. 2019; Soomro and Zhang 2015). Although different parties have different definitions of the PPP project failure under various interests (Soomro and Zhang 2015), PPP contract failure, including distress or eventual termination of the contracts, is an extreme form of the poor performance of a PPP project, which has been considered as serious trouble for both public agencies and foreign investors (Cunha Marques and Berg 2011; Nose 2014). In other words, PPP contract failure is one type of PPP project failure. Fig. 1.2 demonstrates the distribution of failed contracts in developing countries since 1990.

Fig. 1.2. Geographical distribution of PPP contract failure cases since 1990 (data source: PPI database)

Once a PPP contract is canceled, public agencies may unavoidably bear unexpected financial burdens by redeeming private shares, and the private sectors may receive a bad reputation (Demirel et al. 2019; Zhang and Xiong 2015). Currently, a large volume of research has focused on finding the success triggers of a PPP project (Ahmadabadi and Heravi 2019; Ameyaw and Chan 2015; Hsueh and Chang 2017). Díaz (2020) pointed out that the factors for PPP contract failure differ from those for PPP success, however, the research on the factors of PPP contract failure is lacking (Zhang and Tariq 2020). Overall, three gaps have been detected.

First, the influence of host countries' PPP experience on PPP contract failure has not been deeply studied. Avoiding the failure of PPP contracts not only requires proper planning, execution, and monitoring but also the experience from the governments (Marcelo et al. 2017). Learning from experience to improve future infrastructure PPPs has attracted a lot of attention from policymakers, financiers, implementers, and private sector stakeholders (Marcelo et al. 2017). For instance, the experience in collaboration over the planning and implementation of infrastructure can play an important role in peacefully and effectively solving divergent interests (Jones and Howarth 2012). Many reports and papers focus on the lessons and experiences learned from the previous PPP projects by case studies. But these qualitative results cannot be used to measure the impact of countries' experience on contract failure from a quantitative perspective. That is to say, how experience impacts the failure of the contract is abstract. A more detailed model is expected to find the extent of the influence of PPP experience on contract failure.

Second, the influence of involved foreign countries' knowledge on PPP contract failure has been neglected. The success of PPP projects is heavily dependent upon the interconnections of expertise from different parties engaged in the project (Kwawu et al. 2010). It is, therefore, hard for some countries, especially developing countries, to implement a successful PPP transaction because of the poor PPP knowledge in both public and private sectors (Liu and Wang 2018; Neto et al. 2020; Song et al. 2018). PPP knowledge here refers to the knowledge required to implement and manage a PPP project, such as management experience, technology, financial knowledge, legal knowledge, and construction knowledge (Ni et al. 2018; Sun et al. 2019). The knowledge base of an organization is likely to be effectively enhanced by absorbing the knowledge from other organizations (Sun et al. 2019). Successful knowledge transfer among various project members can help in avoiding failure risks, mitigating potential risks, fostering innovation, and improving project performance (Biygautane et al. 2019; Ni et al. 2018). With the development of the world, the global PPP marketplace has been established (Guevara et al. 2020). More and more international companies have been selected to assume diverse responsibilities in the PPP project that is based in foreign countries, which is a good chance for different countries to learn from each other. Despite relevant literature has focused on the knowledge

transfer in PPP domains including knowledge transfer mechanism in a project team (Sun et al. 2019), critical factors affecting knowledge sharing (Zhang and He 2015), and knowledge transfer across different projects (Zhou et al. 2020), few studies have provided enough information about the PPP knowledge transfer among different countries at the global level.

Finally, as previously mentioned, most research is focused on detecting the success factors of a PPP project. Although the identified factors could be useful for sponsors to organize a successful PPP project, determination of the outcome of a PPP project requires efforts from the experts, leading to subjective and error-prone results. Artificial intelligence (AI) has proved to be a promising solution to assist in decision making, which is usually a classification problem, towards higher efficiency in the construction management field (Cao and Ashuri 2020; Zelenkov 2019). AI technology has been used in the PPP domain by some scholars. For example, it has been used for predicting the completion risk of a PPP project (Owolabi et al. 2018), as well as disputes between the public authority and private partner (Chou and Lin 2013; Zheng et al. 2021). However, no studies have been found on PPP contract failure prediction based on the previous projects. In a classification problem, the output of the target variable can be several classes, such as success or failure. However, in the conventional models, the misclassification errors are assumed to be equal for different classes. In other words, these machine learning (ML) classifiers are cost-insensitive (Ling and Sheng 2010). It is, however, often not the case for imbalanced classification problems where the class distribution in the data set is skewed (Kaya et al. 2021). More specifically, the class containing the most samples is called a majority or negative class, and the other class is the minority or positive class. The minority class may be neglected attributed to insufficient information. Missing a minority class case is usually worse than incorrectly classifying a sample from the majority class (Brownlee 2020). For instance, in the process of detecting spam email, diagnosing a medical condition, and identifying fraud, missing a positive case is usually more costly than misclassifying a negative one.

Cost-sensitive learning is a type of learning that considers the cost of misclassification errors (Feng et al. 2020). The primary difference between cost-sensitive learning and cost-insensitive learning is that the first one treats different

misclassifications differently. The cost for labeling a positive sample as negative can be significantly different from the cost for labeling a negative sample as positive, which is also named the class-dependent cost-sensitive classification (Zelenkov 2019). Unlike conventional methods, the goal of cost-sensitive learning is to minimize the total cost of misclassification errors. Although the class-dependent cost-sensitive models can distinguish the difference between the cost of misclassifying classes, they have neglected the immense disparities among the costs for misclassified samples in many real-world applications (Zelenkov 2019). For instance, the potential economic loss led by the failure to detect a fraudulent transaction is dependent on the transaction amount in credit card fraud detection (Stolfo et al. 2000). In churn modeling, customers would have different probabilities to abandon the services, causing inconsistent costs corresponding to various misclassifications (Correa Bahnsen et al. 2015; Karuppaiah and Palanisamy 2021). That is to say, the misclassification cost depends not only on the classes but also on samples.

PPP projects are usually designed with various investment sizes accompanied by different debt-to-equity ratios. Once a PPP project fails, the financial impact on the sponsors would vary with each project. The difference in the investment sizes of the PPP contracts should be considered when predicting the final status of the PPP project. The classification problem considering the misclassification costs of samples in the data set is called the example-dependent cost-sensitive (ECS) classification (Bahnsen et al. 2014). The machine learning model using the ECS technology is the example-dependent cost-sensitive machine learning (ECS-ML) model. However, it has not been applied in the PPP domain. There is a need to explore how this classifier can be implemented to predict the PPP contract failure.

In summary, the main gaps found in the current literature review are: 1) a limited number of determinants of the PPP contract failure have been identified and studied with some important factors neglected, 2) the impact of countries' PPP experience on PPP contract failure is not explicitly and quantitatively highlighted, few studies have contributed to the quantification of countries' PPP experience levels, 3) the importance of the countries that are involved in the projects has not been considered, which can influence the correct partner selection for a PPP team, and 4) the current ML models cannot consider the cost of misclassifications, which may have bad

influence on the decision-making process when being applied in PPP contract failure prediction.

The primary questions that will be addressed in this thesis are:

- 1) How could the PPP experience of developing countries be measured based on the existing data sets?
- 2) How could the PPP experience levels of a developing country be qualified to generate an intuitive index?
- 3) How could a PPP knowledge transfer network be developed based on real-world unstructured data to quantify the importance of a country in transferring PPP knowledge and reveal the PPP knowledge transfer paths among countries in a region and between regions?
- 4) How could a PPP partner be selected based on their roles in transferring PPP knowledge?
- 5) What are the main factors of the PPP contract failure in different PPP sectors?
- 6) How could an ECS-ML model be implemented to forecast the final status of a PPP project?
- 7) How could the appropriate models be developed to predict the status of a PPP contract from both accuracy-oriented and profit-oriented perspectives?

1.2 Research Objectives

The main aim of this thesis is thus to find out the main triggers of the contract failure of a PPP project and predict its final status through the classification ML model based on the given conditions including the project-specific factors and investment environment of a country. Furthermore, the newly proposed factors that may affect the PPP contract failure will be quantified before the development of the ML model, such as the PPP experience levels of a country, and the importance of the countries that have been involved in a project. As a result, based on the previously mentioned questions, the specific objectives of this study are shown below:

- a) Quantifying developing countries' PPP experience levels.
- b) Quantifying countries' importance in transferring PPP knowledge around the world.

- c) Combining the previously proposed factors with other existing project-specific and country-specific variables to predict the final status of a PPP contract using both traditional ML models and ECS-ML models.

Objectives (a) is designed to answer questions (1) and (2), objective (b) is designed to answer questions (3) and (4), and objective (c) is designed to answer questions (5), (6), and (7).

1.3 Significance and Contribution of the Research

First, by quantifying countries' PPP experience levels considering the uncertainty in the real-world data, this thesis may be an important starting point for ongoing research on PPP experience. Categorization of PPP experience levels can provide support not only for investors in choosing the right investment direction by gaining knowledge about which countries are more experienced in one sector but also for PPP proponents in promoting the development of economies in developing countries by providing more assistance to countries with low experience levels.

Second, by proposing a novel data-driven social network analysis (SNA) method to study the dynamic flow of PPP knowledge from mature markets to emerging markets, this thesis can guide public sectors and private investors in decision-making by revealing the knowledge transfer paths and the most crucial countries. In other words, the results will contribute to the correct partner selection process.

Third, by using the ECS-ML and traditional ML models to predict the outcome of a PPP project, this thesis can serve as a reference for public agencies and private sectors in the feasibility study in the early planning stage to determine whether the project is feasible or not. Besides, sound actions and strategies toward successful PPP projects can be put forward based on detected failure factors and their relative importance. Finally, the users can select the ML models from both the statistical and financial metrics, such as recall as well as cost-saving.

In conclusion, as few studies have been found to conduct similar research, this thesis will be an important starting point for future research. The findings in this thesis are expected to support different stakeholders in making decisions and assist in achieving the aims of PPP schemes.

1.4 Novelty of the Research

In this thesis, the PPP experience levels are quantified based on real-world data. When compared with conventional surveys and determinant methods, the Bayesian theorem can detect the PPP experience levels objectively considering the uncertainty of the data set. Moreover, it is the first time that the evolutions of the roles of different countries in PPP knowledge transfer being explored based on SNA. Finally, it is also the first time that an ECS-ML model being used in the PPP domain, particularly in predicting the final status of a PPP project and detecting the failure factors.

Overall, the methodologies adopted in this thesis have never been used in the PPP domain according to the literature review.

1.5 Structure of the Thesis

This thesis contains 8 chapters as illustrated in Fig. 1.3. It is organized as follows:

- 1) **Chapter 1** introduces the background of the research, research questions, research objectives, the significance as well as contributions of the research, and the innovation of the research.
- 2) **Chapter 2** gives some primary concepts in the PPP domain, such as PPP structure and features of PPP models. At the same time, it also briefly reviews the related research works in PPP domains in terms of the quantification of PPP experience levels, the evolution of countries' roles in PPP knowledge transfer, failure factors of PPP projects, and main algorithms in a classification problem.
- 3) **Chapter 3** presents the proposed methodology in this thesis.
- 4) **Chapter 4** develops a framework to quantify the PPP experience levels of developing countries based on the Bayesian hierarchical model and binary segmentation method. Three industry sectors will be exploited, and they are the transportation sector, the energy sector, and the water & sewerage (W&S) sector.
- 5) **Chapter 5** develops a methodology to explore the evolution of the roles of different countries in PPP knowledge transfer. The developments in the importance of both developing and developed countries have been revealed from different perspectives.

- 6) **Chapter 6** applies the traditional ML models, such as random forest and logistic regression, to four various data sets. The results have been compared among various data sets, indicating the effectiveness and importance of introducing the newly quantified factors. Moreover, the failure factors will be discussed based on the model results.
- 7) **Chapter 7** proposes the ECS-ML models. The cost matrix is used to denote the cost of misclassifications for PPP projects, and the performance of the model is evaluated using profit-oriented and accuracy-oriented metrics.
- 8) **Chapter 8** gives the conclusions and implications of the study. Moreover, the future work and limitations of this study are revealed.

Fig. 1.3. Structure of the thesis

Chapter 2 Literature Review

2.1 Introduction

In this chapter, the existing literature from the area of PPP, the current methodologies used to analyze the PPP experience, the roles of various countries, techniques used to forecast the outcome of a PPP project, and the common methods used to handle the imbalanced data sets are reviewed. The works in this chapter form the theoretical basis for developing ML models to forecast the final status of a PPP project.

2.2 PPP Projects

The PPP scheme is considered a new way of providing public services or infrastructures. It aims to relieve the disadvantages of public departments by promoting the efficiency of providing public services. There are many definitions for the PPP around the world in different contexts (Li et al. 2017). However, in a typical PPP model, the long-term relationships among the public departments and the private departments are usually established based on various contracts (Liu and Su 2017).

2.2.1 PPP Models

A PPP structure can be quite complex involving contractual arrangements among different parties including the public agencies, operators, contractors, suppliers, customers, and third parties, as shown in Fig. 2.1. Fig. 2.2 shows the changes in risks and investment for different PPP models. Some main parties are explained below:

- 1) Special Purpose Vehicle (SPV) is established under the agreement between different shareholders or sponsors, and it is the entity that undertakes the project. The agreement details the ownership and management control of the SPV. It is usually called the project company.
- 2) Financiers mean various parties that invest in the project comprising equity and debt. They can be domestic and foreign banks, bilateral institutions, multilateral institutions, and development banks.
- 3) The escrow agent is assigned by the project company and lenders, and it aims to manage an account named escrow account that is used to hold the funds related to the project company, such as revenues and deposits in trust.

Fig. 2.1. A typical structure of a PPP model

Fig. 2.2. Changes in risks and investments for different PPP models

Currently, a series of PPP models have been invented to enable the participation of private sectors. These models may vary depending on the ownership of capital assets, responsibility for investment, and payment mechanism. The payment mechanism is a key element corresponding to the risk-sharing mechanism in a PPP contract. Based on this incentive, five categories of PPP models are classified in the order of increased involvement by the private sector. They are: 1) supply and management contracts, 2) turnkey projects, 3) affermage/lease, 4) concessions, and 5) private ownership of assets. Generally, management contracts are common for existing assets in the water and transportation sectors, affermage/lease contracts are common in the transportation sector, concessions are common in the transportation and telecommunication sectors, while turnkey and private ownership of assets are common in the power sector. It can be seen from Fig. 2.2 that a higher investment

means a higher risk. From the perspective of private investors, a management contract has the least risk and private ownership of assets bring the highest risk.

2.2.2 Structure of PPP Contracts

By randomly combining the above-mentioned features, different types of PPP contracts with many variants can be generated. Table 2-1 and Table 2-2 demonstrate different variants of each type of PPP contract and their basic features, respectively. Fig. 2.3 illustrates the structure of the above-mentioned contracts.

Table 2-1 Variants for each type of PPP contract

Category	Contract
Management contract	Supply or service contract
	Maintenance management
	Operational management
Turnkey	Design-Build-Finance (DBF)
	Build and Finance (BF)
Affermage/Lease	Affermage
Concessions	Franchise
	Concession
	Build-Operate-Transfer (BOT),
	Build-Own-Operate-Transfer (BOOT)
	Build-Transfer-Operate (BTO)
	Rehabilitate-Operate-Transfer (ROT)
Private ownership of assets	Private Finance Initiative (PFI)
	Design-Build-Finance-Operate-Maintain (DBFOM)
	Design-Build-Finance-Operate (DBFO)
	Design-Construct-Manage-Finance (DCMF)

Table 2-2 shows that PPP contracts are mainly different in the type of asset, functions transferred, and the primary source of revenues. There are two types of assets: new assets and existing assets. In other words, the project can be greenfield and brownfield. Besides, the private investors can get the payment from end-users, the government, or both of them. These variables make PPP contracts different from each other and expose a PPP contract to a different probability of failure.

Table 2-2 Three basic features for different PPP contracts

Contract	Type of Asset	Functions Transferred	Payment Source
Management	Existing	Operations and maintenance	Management fees
Operations & Maintenance	Existing	Operations and maintenance	Government
DBF, BF	New	Finance, design, and build	Government
Affermage	Existing	Operations and maintenance	User pays-private party typically remits part of user fees to the government to cover capital expenditures
Franchise	New or existing	May include design, build, and finance, or may be limited to maintaining and operating an asset	User or government
Concession	New or existing	Design, rehabilitate, extend or build, finance, maintain, and operate-typically providing services to users	Usually, the user pays, in some countries, depending on the financial viability of the concession, the private party might pay a fee to the government or might receive a subsidy
BOT, BOOT, BTO	New	Typically, design, build, finance, maintain, and some or all operations	User or government
ROT	Existing	Typically, design, rehabilitate, finance, maintain, and some or all operations	User or government
PFI	New	Design, build, finance, maintain- may include some operations, but often not providing services directly to users	Government
DBFOM, DBFO, DCMF	New	As captured by contract name	User or government

Fig. 2.3. Structure of different PPP models

2.2.3 Comparison of Different PPP Contracts

Good knowledge of the disadvantages and advantages of a PPP contract can make sure an appropriate contract being chosen when implementing a PPP project. Table 2-3 compares the merits of different contract forms.

In Table 2-3, the main advantages are the short period, simplicity to implement, the willingness of the private sectors to invest, and efficiency improvement. Moreover, the main disadvantages are the lack of incentive for private sectors to finish the construction early and operate the project efficiently, as well as additional charges. Therefore, there does not exist a perfect contract that contains all the advantages and avoids all deficiencies. What can be done is to select the appropriate investment direction and partners to lower the probability of disputes in a PPP contract.

Table 2-3 Advantages and disadvantages of various PPP contracts

Contract	Advantages	Disadvantages
Management contract	<ul style="list-style-type: none"> •Short time. •Simple. •More acceptable for water, ports, and airports. 	<ul style="list-style-type: none"> •Difficult to gain efficiency and attract private investment. •Risks are borne by the public sector. •Applicable to existing assets.
Turnkey	<ul style="list-style-type: none"> •Simple. •Contract enforcement is easy to achieve. 	<ul style="list-style-type: none"> •The private sector has no incentive to complete earlier. •Most risks are borne by contractors. •Low private investment for a limited period. •Limited innovation.
Affermage/lease	<ul style="list-style-type: none"> •Short time. •Significant private investment under a longer-term agreement. •More applicable in ports and airports 	<ul style="list-style-type: none"> •Difficult to attract private investment. •Almost all risks are borne by the public sector. •Applicable to existing assets. •Need more regulatory oversight.
Concessions	<ul style="list-style-type: none"> •Private sectors bear more risks. •Can attract more private investment. •More likely to improve efficiency in all phases of the project. 	<ul style="list-style-type: none"> •Complex to implement and administer. •May have fiscal costs to the government. •Long negotiation time. •Need close regulatory oversight. •Contingent liabilities to the government in the medium and long term.
Private ownership of assets	<ul style="list-style-type: none"> •Private sectors bear a significant share of risks. •High level of private investment. •High efficiency and innovation gains. 	<ul style="list-style-type: none"> •Complex to implement and administer. •May have fiscal costs to the government. •Long negotiation time. •High requirements of regulatory efficiency. •Contingent liabilities to the government in the medium and long term.

2.3 Overview of PPP Experience

2.3.1 Quantification of PPP Experience Levels

As the experience is evolving with time, there could be some reflection points that can divide the PPP experience into various levels, whose effects on the performance of PPP projects are diverse (Leigland 2018). Some effort has been committed to the categorization of experience levels by surveys. For example, Queiroz et al. (2014) divided the PPP experience into 5 levels by using PPP Perception Index based on the results from questionnaires. Wang et al. (2019) classified the PPP experience as success or failure according to whether a country has concluded or failed PPP projects. It can be seen that these studies only characterized the PPP experience of a country from a qualitative standpoint. The bounds of these experience levels are, however, not properly identified. Hence, some quantitative methods are proposed by researchers in response to the above problems. For example, Marcelo et al. (2017) interpreted the PPP experience as the number of developed PPP projects in the past decades based on the World Bank (PPI) database. In this method, the location of the change point is determined by visual check, and the influence of experience on the contract failure rate is determined using the piecewise linear regression model. However, the method is subjective and via-based, leading to the misdetection or omission of PPP experience levels. This suggests the need for a quantitative and accurate model to determine the bounds of different experience levels.

The quantification of PPP experience levels could be converted to a change point detection problem, the aims of which are determining the number and locations of change points.

2.3.2 Change-Point Detection Method

Change-points detection can be a challenging task since both the number and positions of change points are unknown but it has been used in many domains, such as finance and crime analysis (Albertetti et al. 2016). The binary segmentation method, which can search the number and locations of change points automatically, is one of the widely cited algorithms in multiple change-point detection processes (Haynes et al. 2017; Olshen et al. 2004). It has been proved to be consistent in detecting the number of change points in a series of sectors, such as hazard rate and

finance (Vostrikova 1981). Moreover, different hybrid methods have been proposed by scholars to increase the estimation accuracy, such as a hybrid of support vector regression and CUSUM method (Lee et al. 2020), as well as a hybrid of support vector machine and fuzzy statistical clustering method (Kazemi et al. 2016). However, in real-world applications, uncertainty in data is unavoidable (Moghadam et al. 2018). For instance, the PPP project database may exclude some PPP projects, causing uncertainty in the number of PPP projects in some countries (Loxley 2013). Several potential limitations exist in the conventional deterministic method in dealing with such kinds of problems, such as unable to detect the uncertainties in the recorded data (Katzfuss et al. 2017; Sharma et al. 2016) and the need for a complete data set for an accurate result (Kalinina et al. 2018).

To relieve these issues, the Bayesian theory provides a direction. The Bayesian theory describes the posterior probability of an event based on the prior knowledge that might be related to the event. It can quantify the uncertainty into a probability distribution because of the probabilistic theory, contributing to the decision-making process (Cai et al. 2016; Hernández and López 2020; Kabir et al. 2018; Zhang et al. 2014). Despite the benefits of the Bayesian approach, one of its disadvantages is that the variance of the posterior probability may be large when analyzing a scarce data set. As a result, the prediction may not be robust enough. In this context, the bounds of the experience levels may be unclear. A Bayesian hierarchical model can be used to solve this problem by enabling the quantification of uncertainty with multiple levels (Ruggieri and Antonellis 2016). The Bayesian hierarchical model has been applied in many areas, such as dam disaster assessment (Kalinina et al. 2018), streamflow prediction (Li et al. 2020), and economics prediction (Meager 2016).

Despite the wide application of the Bayesian hierarchical model in change point detection, there are still two challenges. The first challenge is that there is a lack of prior knowledge of how many change points exist in the data set. To solve this problem, some scholars have assumed the number of change points before detecting their locations (Bherwani et al. 2020; Dehning et al. 2020; Zhao et al. 2019). However, this method may miss the change points or add more change points to the data set. The other challenge is that the choice of priors and hyper-priors has been considered critical in the Bayesian hierarchical model, which may have a substantial effect on

posterior distributions (Mao et al. 2020; Tariq and Zhang 2020). Currently, most studies, however, have used weakly informative or noninformative priors and hyper-priors, which are usually obtained from expert knowledge (Cai et al. 2016; Cai et al. 2020; Gul et al. 2020) or assumptions (Mil and Piantanakulchai 2018). The main disadvantages of these noninformative priors are that they are subjective and contain uncertainty that is larger than plausible parameter value, which might be limited for most practical applications. Therefore, using informative priors in the Bayesian model has been encouraged by some studies (Lee et al. 2020; Lemoine 2019). Although some studies have tried to obtain the hyper-parameters using data-driven methods, they are usually of high computational complexity and are difficult to achieve (Agudelo-España et al. 2020; Fearnhead 2006).

This thesis attempts to propose a hybrid methodology that combines the binary segmentation method and the Bayesian hierarchical model. More specifically, the number and locations of change points obtained from the binary segmentation method will be treated as the informative priors in the Bayesian hierarchical model. As a result, the proposed method not only can consider the uncertainty in the data but also is easy to implement.

2.4 Overview of PPP Knowledge Transfer

2.4.1 PPP Knowledge Transfer and Partner Selection

In general, knowledge transfer focuses on transferring technological platform, market experience, managerial expertise, corporate culture, and other intellectual capital that can improve the companies' competence (Boh et al. 2013). More specifically, during the process of knowledge transfer, the knowledge from one part of an organization (a project team or other organizations) could be transferred to another. The importance of knowledge transfer in the PPP project has triggered the studies in PPP knowledge transfer. Knowledge transfer is a process of movement of different types of knowledge from knowledge supplier to the recipient or from one place to another (Sun et al. 2019). During the process of developing a PPP project, the knowledge transfer can occur among diverse internal groups, including contractors, sub-contractors, legal and financial advisors, and operators, through meetings and discussions (Alashwal et al. 2016; Ni et al. 2018).

However, given the intrinsic complexity of PPP knowledge, the successful transfer of PPP knowledge is often not an easy job (Liu and Wang 2018). Most PPP knowledge is tacit, such as experience and know-how (Zhang and He 2015). In contrast to explicit knowledge, the tacit counterpart is unlikely to be articulated (Fritsch and Kauffeld-Monz 2008). The process of implicit knowledge transfer forms a social network, and it relies on the quality and quantity of social interactions (Schmidt and Hunter 1993). It is, therefore, of paramount importance to establish a project team filled with efficient communications and interactions. However, international PPP shows an evolutionary trend, causing the dynamics of the structure and behavior of actors in the knowledge transfer network (Cheng et al. 2020). Although a capable organization can transfer its domain knowledge to other organizations more effectively than that of less ability (Yan and Gray 2001), it is usually difficult to select correct partners to establish a competitive team. Additional research in PPP knowledge management, such as PPP knowledge transfer, has been suggested (Cui et al. 2018).

These scholars are mainly concentrated on the knowledge transfer within an organization, few studies have considered the background of a company's headquarters. However, knowledge transfer needs support from the right type of structure, culture, and strategy (Jain et al. 2015; Mba and Agumba 2018; Siakas et al. 2010). As different countries differ in their legal traditions, economies, cultures, and institutions, the organizations located in these countries are usually possessing different levels of reliability, experience, capabilities, and willingness to transfer the knowledge (Ni et al. 2018; Zhou et al. 2020). Moreover, most studies are making use of empirical information by surveys and questionnaires (Javernick-Will 2012; Ni et al. 2018; Zhang and He 2015; Zhou et al. 2020). The main shortcomings of these methods are that the information may be subjective owing to the misinterpretation of the problems by the respondents and personal matters of the respondents (Dalati and Gómez 2018). When these outcomes are used to choose an appropriate partner for better knowledge transfer, decision-makers need to judge whether the candidates match the criteria of a good knowledge source. Conflicts and biases that can mislead the decision-making process are likely to be caused. It indicates a need for an

objective and real-world data-based index that allows for the determination of the capability of a partner in the knowledge transfer process (Asenova and Beck 2010).

2.4.2 SNA in Project Management and Knowledge Transfer

SNA can help in this regard. SNA is a process of denoting the network of objects as a graph, which has been widely used in social and behavioral sciences (Borgatti et al. 2009; Wasserman and Faust 1994). Many scholars have analyzed the knowledge transfer using SNA in the construction industry. It has been used to model the knowledge transfer path and the roles of various parties in many sectors. For example, SNA has been used to examine the knowledge flow in delivering sustainable buildings (Schröpfer et al. 2017), check the collaborative relationships among different stakeholders (Wang et al. 2020), explore the interactions between design team members (Herrera et al. 2020), choose loaders (Zhang et al. 2020), identify key factors causing the project delay (Zarei et al. 2018), and reduce the safety problems (Abbasianjahromi and Etemadi 2019).

When compared with other methodologies such as structural equation modeling (Zhou et al. 2020) and significance analysis (Zhang and He 2015), SNA can reveal the social position of an organization and the structure of network relationships at the macro-level and micro-level, respectively (Biygautane et al. 2019; Smelser and Baltes 2001). SNA contains nodes and relationships. The nodes can be an organization, a project, or even a country, while the type of relationships can be that of collaboration, the process of exchanging knowledge. The characteristics of the network, such as the importance of an actor and flow of information along the edge, can be investigated by a series of metrics such as network size, density, degree centrality, and PageRank (Hassan et al. 2019; Kim and Hastak 2018; Lee et al. 2018). Besides, the dynamics of the roles and their relationships can be easily obtained by comparing different metrics of each network (Castillo et al. 2018; Wang et al. 2020).

Due to these advantages, the application of SNA in PPP domains has also attracted some attention. For instance, studies have been conducted to find the most active actors in the UK PPP secondary equity market (De Biasio and Murray 2017) and PPP projects (Chowdhury et al. 2011; Guevara and Garvin 2017), the most important risk factors in PPP projects (Wang et al. 2020), and the changes in the structure of PPP

stakeholder network (Guevara et al. 2020; South et al. 2018). Although these examples verified the possibility and feasibility of analyzing the networks in PPP domains using SNA, little attention has been paid to establishing a social network for analyzing the collaboration among different countries and finding the most influential actors in PPP knowledge transfer confronting an increasingly growing PPP environment (Al Hattab and Hamzeh 2015).

2.5 Prediction of PPP Contract Failure

The identified critical success or failure factors can only be used to guide the organization of a PPP project. The effect of these factors on the outcome of a PPP contract is not obvious, especially considering the interrelationships among different factors. Therefore, to lower the risks of PPP contract failure, it is important to proactively forecast the results of a PPP contract.

2.5.1 Failure Factors of PPP Contracts

Currently, many studies have concentrated on detecting the critical success factors (CSFs) to ease the process of feasibility analysis of a PPP project. These CSFs can be the selection of proper projects, supports from the domestic government, a transparent bidding process, and risk allocation (Ahmadabadi and Heravi 2019; Hsueh and Chang 2017; Tiong 1996). Nevertheless, the in-depth literature on the determinants of the contract failure of a PPP project is scant. Knowing the key factors triggering the contract failure and how they influence the final status of a PPP project can help PPP promoters devise sound strategies to avoid the initiation of a PPP project that has a high probability to suffer contract failures.

PPP projects are intricate due to their unique characteristics, such as the lengthy contract and complex relationships between the private sectors and government agencies (Abdullah and Khadaroo 2020). From the perspective of contract form, a PPP project can adopt a BOT contract, a lease contract, and a build own & operate (BOO) contract. From the perspective of project type, a PPP project can be a greenfield project and a brownfield project. From the perspective of disciplines, a PPP project can be a transport project, an energy project, and a W&S project. These project-specific factors make PPP projects different from each other. In other words,

the probability of contract failure of a PPP project should depend not only on the investment environment but also on its properties.

To solve the above-mentioned issues, some related studies intend to identify the factors driving the contract failure of a PPP project based on real-world data sets. For example, Harris and Pratap (2009) revealed the key factors that influence the cancellation of PPP projects by analyzing the PPI project database, such as the previous experience of the host countries and project sectors. Mansaray (2018) obtained the main risks associated with PPP contract failure by utilizing the PPI database, such as corruption and governance variables. Although these studies can detect the failure factors of a PPP contract, they cannot be used to predict the final status of an existing PPP project or a project to be initiated given the combinations of various variables. When applying these criteria to evaluate the feasibility of a PPP project, the main challenges are analyzing and matching the criteria with the project background. The assessment results tend to be subjective and are highly dependent on the knowledge and even interests of the decision-makers. In other words, rather than knowing the exact probability of the contract failure of a project, the decision-makers can only obtain a qualitative result by referring to these factors. As a result, they may implement a project that is more likely to fail while abandoning some promising projects. To date, there are only limited quantitative studies that have tried to predict the final status of a PPP project. For example, Ng et al. (2010) tried to predict whether the PPP projects in Hong Kong could meet the requirements of different stakeholders by using the structural equation model. Akbari et al. (2020) proposed a decision support system to predict the success of infrastructure projects based on sustainable success factors. However, these models still need some prior knowledge from users such as the success criteria of different partners, and they are not sufficient and accurate enough.

2.5.2 Machine Learning Methods

ML approach has shown a potential solution to these problems, which has been extensively applied to the PPP domain by some authors. For instance, Chou and Lin (2013) have used ensemble ML models to predict the disputes in PPP projects before they happen. Owolabi et al. (2018) forecasted the potential delay in PPP projects using a series of ML models, such as regression trees, the support vector machine,

and the deep neural network. Wan and Fang (2020) established the risk evaluation index system for expressway PPP projects by adopting the support vector machine model. When disputes, cost overruns, and construction delays happen during the PPP contract, negotiations might be held between the public and private sectors. However, if the negotiation fails, PPP contract failure would occur (Tariq and Zhang 2021). The result of PPP contract failure is, therefore, worse than that of the dispute and overrun of time as well as cost. Although the current studies imply the feasibility of using ML models in the PPP domain, no studies have been carried out on the prediction of the success or failure of a PPP contract.

In this context, some existing literature tried to examine the primary failure factors of a PPP project. For example, Song et al. (2018) detected eleven primary factors of early termination of Chinese PPP contracts based on case studies, such as improper operation and government payment default. Tariq and Zhang (2020) revealed 60 critical failure determinants in water PPP projects from a global perspective by reviewing 35 different projects. Dolla and Laishram (2020) found 13 negative factors for Indian municipal solid waste PPP projects based on questionnaires, such as lengthy delays due to politics. It can be found that most current research is about specific sectors, regions, and countries. The failure factors in one place may differ from the ones in other places, which may mislead the decision-making process (Kwofie et al. 2016). Moreover, these studies have been conducted based on case studies and surveys. The result may contain errors due to the mistakes made during the surveys and the bias introduced by the respondents.

When compared with conventional statistical methods, the ML model focuses more on the predictions of the result rather than detecting the relationships between variables (Rajula et al. 2020). Unlike statistical techniques that have to be used under the given rules, the ML model can learn from the data by giving the inputs and outputs.

2.5.3 Classification of Imbalanced Data

There may be an unneglectable difference between the numbers of the samples of each class in a data set, which will be assumed to be roughly balanced when using the standard ML algorithms (Wong et al. 2020). Some techniques have been employed to increase the accuracy of the models. Currently, the most common

methods to handle the imbalanced problem can be categorized into data-level and algorithm-level methods.

From the perspective of data-level methods, the imbalanced data sets will be converted into balanced ones by resampling techniques, which include oversampling technique and undersampling technique. When compared with other methods, data-level methods, such as Synthetic Minority Oversampling Technique (SMOTE), are simpler to be implemented (Fernández et al. 2018). Oversampling technique is used to duplicate the samples of minority classes, while the undersampling method will delete samples from majority classes (Yu et al. 2018). These techniques have been used in processing signals (Shao et al. 2021), predicting protein-protein interaction sites (Wang et al. 2019), and credit risk evaluation (Shen et al. 2021). Table 2-4 lists some common oversampling techniques. However, the traditional resampling methods are vulnerable to outliers and the number of minority classes. Some novel resampling methods are proposed to overcome these disadvantages. For example, Maldonado et al. (2019) applied a new distance metric for the SMOTE oversampling strategy to handle high-dimensional data sets. Pouyanfar et al. (2018) designed a new model that dynamically modifies the number of samples from each class during the training process. Ramentol et al. (2012) combined the oversampling and undersampling methods to protect the information from loss. Koziarski (2020) used a Radial-Based Oversampling method to mitigate the limitations encountered in the undersampling method.

Table 2-4 Some of the common oversampling techniques

Oversampling techniques	Description
Random oversampling	Randomly duplicate some of the original samples of the minority class.
Synthetic Minority Over-sampling Technique (SMOTE)	Generating new observations by interpolating between observations in the original data set.
Adaptive Synthetic (ADASYN)	Generating samples next to the original samples which are wrongly classified using a k-Nearest Neighbors classifier.

The data-level methods only attempt to change the distributions of both majority and minority classes, and they cannot change the basic principle of the traditional ML algorithms, which assume that all misclassification errors carry an identical cost

(Correa Bahnsen et al. 2015). More specifically, the conventional classification methods are accuracy-oriented, focusing on minimizing the misclassification errors. A sample is thought to have been wrongly detected if its predicted label is different from the true label. However, this is not the truth for many practical problems. Therefore, some algorithm-level methods have been proposed.

2.5.4 ECS Machine Learning Models

The principal algorithm-level method is to adjust the existing algorithms to avoid biased classification results. For example, Ohsaki et al. (2017) proposed a confusion-matrix-based kernel logistic regression model by considering the mean of the various evaluation criteria as the objective function. Jimenez-Castaño et al. (2020) proposed an enhanced twin support vector machine to improve the performance and reduce the training time of conventional models. Wang et al. (2019) proposed a dynamic curriculum learning method to adjust the loss weight during the training process. Moreover, ensemble models have also been widely adopted. Ensemble models contribute to performance improvement by combining the results of monolithic classifiers (Alves Ribeiro and Reynoso-Meza 2020). The common types of ensembles include Bootstrap aggregating such as random forest, boosting such as XGBoost and LightGBM, and stacking.

Among the newly proposed algorithms, one of the most popular ones is the cost-sensitive classifier, which associates different costs to each class. Instead of using the error-drive evaluation metrics, the objective of a cost-sensitive classifier is to minimize the misclassification cost (Jia et al. 2019). For example, the cost-sensitive model has been used to predict product failures to reduce production costs and guarantee product quality (Frumosu et al. 2020). It has also been used to handle the class imbalance problems in the business area such as direct marketing and default payment (Wong et al. 2020), manufacturing processes such as detecting the abnormal control chart patterns (Fuqua and Razzaghi 2020), and the medical field such as identifying kidney cancer (Shon et al. 2020). Despite the ability to consider different costs for various classes, the cost-sensitive algorithms treat the cost for each type of misclassification error the same. In other words, the cost is related to the labels rather than the samples in the data set.

The ECS-ML model is a potential solution to consider the cost for each misclassified sample. Various classifiers have been created to improve the predictive performance of the existing classifiers, such as the ECS AdaBoost (Zelenkov 2019), ECS logistic regression (Bahnsen et al. 2014), ECS support vector machines (Iranmehr et al. 2019), and ECS decision trees (Correa Bahnsen et al. 2015; Mac Aodha and Brostow 2013). Due to its merits, the ECS-ML model has been applied in predicting the potential tax return defaulters (Mehta et al. 2020), credit ratings (Bahnsen et al. 2014; Wang et al. 2020), and loan evaluation (Xia et al. 2017). These applications have proven the significance of the ECS-ML model. However, most of the current ECS classifiers are based on complex calculations and require high programming skill levels, impeding its extensive application in the management and business areas. Besides, the application of this type of classifier in the PPP domain remains unexplored. In this research, the ECS-ML models will be implemented by customizing the loss functions of the current algorithms in the existing libraries.

2.6 Summary

First, for the analysis on the PPP experience of a country, most of the current studies are based on the qualitative perspective. For example, questionnaires and surveys may be used to obtain the experience levels of a country. However, the results may be subjective. The users still cannot know the experience levels of a country intuitively. Therefore, a quantitative metric is needed to have a good understanding of the experience level of a country.

Besides, a project team can be competitive if strong team members have been involved in it. A strong team member can bring advanced PPP knowledge of its headquarters, such as management experience, construction technology, and financial knowledge, to the project team. As a result, a strong project team can help to ensure the success of a PPP project. However, different countries have different levels of PPP knowledge and various roles in transferring PPP knowledge around the world. Having a clear view of how PPP knowledge is transferred around the world can contribute to the correct selection of a partner. Few studies on PPP knowledge transfer around the world, however, have been found.

Finally, the contract failure of a PPP project can cause unpredicted impacts to both the public and private sectors. For example, the public agency may have to pay more money to buy back the project, and the private sector may gain a bad reputation. By proactively predicting the final status of a PPP project, various parties can decide whether to initiate or invest in the project or not. Besides, proper risk mitigation measures can be used to make the project more likely to succeed. The ECS-ML models can classify the imbalanced data set by minimizing the misclassification costs. Although it has been developed and applied in other areas, it has not been used to predict the final status of a PPP project. This research will deploy the applicability and feasibility of ECS-ML models in the PPP domain.

Chapter 3 Research Methodology

The research methodology is the scientific procedure or technique used to identify and analyze information about a topic, as well as discover the answers to questions. To achieve the objectives of the research, the selection of appropriate methodologies is imperative. The basic types of research can be descriptive or analytical, applied or fundamental, quantitative or qualitative, as well as conceptual or empirical. Based on the above-mentioned research types, the research approach can be divided into the quantitative approach and the qualitative approach (Kothari 2017). This chapter has compared and elaborated on the difference between research methodologies, based on which the appropriate methodologies are selected according to the background of the problems. Finally, the data sources, data collection methods, data preprocessing methods, and data analysis methods are discussed.

3.1 Research Design

The main objective of this research is to predict the final status of a PPP contract using the ECS-ML models considering various existing project-specific and country-specific factors, as well as the newly proposed indicators. To effectively address the research problems and achieve the research objectives, the research design is needed to provide a proper framework for the research (Jilcha Sileyew 2019).

The whole workflow has been shown in Fig. 3.1. The whole thesis includes 10 steps: 1) gap identification, 2) research problems and objectives, 3) literature review, 4) research design & methodology, 5) data collection & preprocessing, 6) quantification of developing countries' PPP experience levels, 7) quantification of developed countries' importance, 8) predicting PPP contract status using conventional ML models, 9) predicting PPP contract status using ECS-ML models, and 10) conclusion & recommendation. These ten steps are explained as follows.

- 1) **Gap identification.** Gaps in the current research are obtained in this step, the main gaps include: 1) PPP experience level has not been quantified although it is an important factor for the success of a PPP contract, 2) there is no direct index for reference when selecting a partner for a PPP team, which is usually achieved by checking track records, and 3) prediction of the PPP contract status is based

on the experience of the experts, ML models have never been adopted under the big data era. This step has been finished in Chapter 1.

- 2) **Research problems and objectives.** To narrow the gaps in the current research, some research tasks have been proposed, which can contribute to the achievement of the main objectives. This step has been finished in Chapter 1.
- 3) **Literature review.** Literature reviews are designed to provide an overview of sources that have been adopted when conducting a particular topic. It is a theoretical foundation to gain enough knowledge about the latest status and tendency of the topic, which is vital to research on PPP contract failure, quantification of PPP experience, and evolution of roles of different countries in transferring PPP knowledge. In this thesis, the sources of literature are mainly from journal papers, conference papers, books, and reports from governments along with various banks. Detailed reviews have been carried out on the structure of PPP, features of the different PPP contracts, different factors that may influence the performance of a PPP project, current methods in quantifying PPP experience as well as countries' importance, contract failure prediction, and needs of improvement of current works. By a deep exploration of existing studies and corresponding methodologies, the gaps in the current research have been found. As a result, newly advanced methodologies are developed to improve the existing conclusions and propose new findings. This step has been finished in Chapter 2.
- 4) **Research design & methodology.** In this step, the study area, data sources, data collection methods, and data analysis methods are given. The primary study area of this thesis is the developing countries that have experience in developing PPP projects. The data sources are the PPI database (World Bank 2019a), World Development Indicators (WDI) database (World Bank 2019b) and Worldwide Governance Indicators (WGI) database (World Bank 2019c), which are collected and processed by the author. Besides, the data analysis method is the quantitative method, including the Bayesian hierarchical model, SNA, and various ML models. This step will be finished in Chapter 3.
- 5) **Data collection & preprocessing.** The data used in this research can be directly reached from the website. Moreover, data preprocessing are conducted and it guarantees the data is appropriate for further analysis. The variables collected

from the above-mentioned databases are given in Chapter 6. This step will be finished in Chapter 3.

- 6) **Quantification of developing countries' PPP experience levels.** In this step, the stochastic analysis is adopted to take into account the uncertainty in the real-world data. As a result, the PPP experience levels of each country in different sectors are denoted by a specific Likert scale, which can provide an intuitive index for decision-makers. This step will be finished in Chapter 4.
- 7) **Quantification of developed countries' importance.** Quantitative analysis (QA) is used to provide the dynamic evolution of the PPP knowledge transfer network from a global perspective. At the same time, the importance of each country in transferring PPP knowledge is converted to a series of quantitative indexes, such as centralities. This could contribute to the process of partner selection for a PPP team. This step will be finished in Chapter 5.
- 8) **Predicting PPP status using conventional ML models.** To predict the final status of a PPP project based on different factors from the real world and the factors from the last two sections, a series of ML models are adopted on different data sets under different data balancing techniques. By introducing new factors, the predicting accuracy is expected to be improved when compared with that of the original data set. Moreover, the primary failure factors of the PPP contract in different sectors are studied quantitatively. This step will be finished in Chapter 6.
- 9) **Predicting PPP status using ECS-ML models.** Before implementing the ECS-ML models, the cost matrix and cost-saving are defined. The new model can improve the accuracy of the results for imbalanced data sets by decreasing the cost of the misclassifications. Moreover, the results of the model are evaluated from a financial perspective rather than the conventional statistical metrics, such as AUC or F_1 score. This step will be finished in Chapter 7.
- 10) **Conclusion & recommendation.** The overall results of the research are summarized. Besides, future works are highlighted. This step will be finished in Chapter 8.

Fig. 3.1. The workflow in this research

3.2 Methods of Data Collection

To achieve the objectives of this research, quantitative methods have been used. The data used is the existing database from the World Bank website. The infrastructure sectors (study area) and data sources are introduced in this section.

3.2.1 Infrastructure Sectors

In this research, the PPP projects in the transportation sector, W&S sector, and energy sector from developing countries are studied. The main reason is that most developing countries have poor PPP ability when compared with developed countries. Therefore, it is vital to empower the developing countries the ability to develop and manage the PPP projects for the aim of economic development. Among various sectors, the energy sector, transportation sector, and W&S sector are the most common sectors that adopt the PPP scheme. Therefore, these three sectors have been selected as the main study areas.

3.2.2 Data Sources and Collection

Based on the definition of PPP experience, the number of PPP projects developed by a country is expected to be known to quantify the PPP experience of a country. Therefore, the World Bank PPI Project Database would be a pertinent data source. It contains records for public infrastructure projects that have reached financial closure in low- and middle-income countries since the 1990s. The main sources of the PPI database are commercial news databases, publications, government reports, and press releases (Xiao and Lam 2020). It has been the primary information source for analyzing PPP projects in developing countries for many publications due to its reliability and integrity (Fay et al. 2019; Soomro and Zhang 2016; Wang et al. 2019; Xiao and Lam 2020).

The projects in the database are within the transportation, Information & Communications Technology (ICT), energy, W&S, and municipal solid waste (MSW) sectors. Each sector includes several subsectors, for example, transportation projects contain airport, railroad, seaport, and toll road projects. PPI database stores the detailed information of each recorded project, covering project country, region, project status, financial closure year (*FCY*), project type, and many other variables. Besides, there is a detailed description for each project, such as information on the project structure, project timeline, and the sponsor name.

Generally, factors that determine the final status of a PPP project can be categorized into four categories. They are project-specific factors such as project types, institutional factors such as control of corruption, legal factors such as rule of law,

and macroeconomic factors such as gross domestic product (GDP) as well as consumer price index (CPI) (Díaz 2020; Ng et al. 2010; Zhang et al. 2016). The project-specific factors are from the PPI database. The institutional and legal factors are obtained from the WGI database. WGI provides 6 indicators to measure the quality of governance based on the survey results from enterprises, citizens, and experts. These indicators are voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption. The macroeconomic factors are from the WDI database. It contains the 1600 time series indicators for 217 economies, of which some can date back to 50 years ago. Nine distinct indicators have been used, such as GDP deflator, GDP per capita, and tax as GDP.

As a result, four data sets are used for data analysis, as shown in Table 3-1. In “Data1”, the project-specific factors are from the PPI database. In the context of ML, each project is an observation of the data set, and the project variables are named attributes. In “Data2”, the number of PPP projects of a developing country in each year is treated as a new factor, which has been treated as the PPP experience of a country in most current studies. In “Data3”, the PPP experience levels obtained in Chapter 4 are used to denote the PPP experience of a developing country. In “Data4”, indicators of both developing and developed countries’ importance in transferring PPP knowledge, which have been calculated in Chapter 5, are considered.

Table 3-1 Data sets that are used for this thesis

Name of data set	Factors in the data set
Data1	Project-specific factors Country-specific factors
Data2	Data1+Number of PPP projects in each year by a country
Data3	Data1+PPP experience levels
Data4	Data3+Countries’ importance

To have a clearer view of the features of each data set, Fig. 3.2 shows the process of establishing different data sets by adding new factors. Only important factors are used to demonstrate the process with common factors removed. It can be seen that Data4 contains the most features, while Data2 and Data3 have the same number of features. The difference between Data1 and Data2 is that the number of projects in each sector

Fig. 3.2. Process of combining data sets

when a country is developing a project is added. The difference between Data2 and Data3 is that the newly added factor in Data2 has been replaced with the PPP experience levels obtained in this research. Moreover, the project year is also considered when creating the data sets. However, these data sets are not complete. For instance, the contract period and type of a PPP project may be missing, which have to be handled before feeding them into a data mining model. Data exploration and data selection are carried out to further select the appropriate data for analysis in the next section.

3.3 Data Preprocessing

This section introduces the process of data exploration and data cleaning, the detailed preprocessing process are given in corresponding chapters.

3.3.1 Data Exploration

The PPI database contains 7096 PPP projects in developing countries, which exist in 5 PPP sectors. Table 3-2 illustrates the number of PPP projects in each sector.

Table 3-2 The number of PPP projects in different sectors

Sector	Subsector	Number of projects	Total number
Energy	Electricity	3289	3599
	Natural Gas	310	
ICT	Telecom	134	134
MSW	Collection and Transport	93	418
	Integrated MSW	47	
	Treatment/Disposal	278	
Transport	Airports	158	1893
	Railroads	140	
	Seaports	431	
	Toll roads	1164	
W&S	Treatment plant	659	1052
	Water utility	393	

The distribution of PPP projects shows an unequal trend in different sectors and regions. Besides, some countries have a lot more PPP projects than other countries in every sector. Table 3-2 indicates that the energy sector has the most PPP projects, while the ICT sector has the fewest projects. Moreover, the recorded PPP projects appear in 6 different regions, they are East Asia and Pacific (EAP), Latin America

and Caribbean (LAC), South Asia (SA), Europe and Central Asia (ECA), Sub-Saharan Africa (SSF), as well as the Middle East and North Africa (MENA). The number of PPP projects in these regions is 2477, 2031, 1343, 589, 454, and 202, respectively. It can be concluded that both EAP and LAC regions have a tremendous number of PPP projects. Besides, China, India, and Brazil are at the top of the ranking of countries with the largest number of PPP projects.

The status of these PPP projects has been divided into 4 categories, they are active, concluded, canceled, and distressed. Active is for the projects that are under construction or operation, concluded is for the project of which the contract period has expired without being renewed or extended, canceled projects are the projects where the private sector has dropped out before fulfilling the contract terms, and distress happens when contract authority or the operator has requested contract termination. Besides, 93.38% of the recorded projects are active and only 2.73% of them are successfully delivered. The canceled and distressed projects account for 3.04% and 0.85%, respectively. To have a clearer view of the duration between the dates when the project status changed (*DSU*) and the *FCY* for a project, a variable named Duration (*D*) is defined. Both *DSU* and *FCY* of a project could be obtained from the PPI database. Therefore, *D* denotes the duration between the financial closure of a project and the date when the current status of a project is changed. For example, the status of a project may be changed to distressed or active. It can be calculated by Eq. (3.1).

$$D = DSU - FCY \quad (3.1)$$

The number of projects with both *FCY* and *DSU* available is 5291. The average *D* for canceled projects, distressed projects, concluded projects, and active projects are 5.75 years, 8.05 years, 10.08 years, and 1.93 years, respectively. The smaller average *D* for active projects indicates that more PPP projects have been developed recently.

3.3.2 Data Cleaning

According to the previous research, the cancellation and distress of the contracts are all treated as contract failure (Marcelo et al. 2017; Marques and Berg 2011). However, as the final status of a PPP project's contract can only be observed and determined when it happens, it is extremely difficult to determine whether the final status of an

active project will be a success or not. Besides, some countries have developed more PPP projects when compared to other countries. A bad effect on the quantification of experience levels of countries with less PPP experience will be caused due to the lack of observables at these experience points. These make the data selection necessary. Fig. 3.3 shows the distribution of D of part contract failure projects, and Fig. 3.4 presents the top 7 countries with the most PPP projects in the energy, transportation, as well as W&S sectors. In Fig. 3.3, the histogram represents the frequency of the D that falls into each bin. Generally, the frequency is converted into probability. The curve is the probability density function (PDF), which is fit using the histogram to highlight the shape of the probability distribution.

Fig. 3.3. Distribution of the duration between FCY and DSU in the contract failure project ($D > 0$)

Fig. 3.4. Top 7 countries that develop the most PPP projects in different sectors

Three standards Standard I-III are followed to select the final data:

- Standard I. All canceled projects, distressed projects, concluded projects, and the active project whose duration D is larger than a threshold δ will be chosen first.

According to the research by Marcelo et al. (2017), δ can be defined based on the average D of contract failure projects. The total number of contract failure projects with D available is 227. It is clear from Fig. 3.3 that the average value is 5.61 years, the mode is 6.17 years, and the maximum value is 17.91 years. Thereafter, δ will be 5.61 years. The latest DSU in the PPI database is 2020-02-05, which is chosen as the last date that the status of the project is updated. Therefore, any active project that achieves financial closure after 2014-07-01 will be neglected. As a result, 5112 projects, including 216 canceled projects, 60 distressed projects, 194 concluded projects, and 4642 active projects, are selected under this standard. If the mode is selected as the δ , the project number will be 4948, which would cause information loss when training the machine learning models, influencing the accuracy of the model.

- Standard II. PPP sectors with a small number of projects will not be considered. Information scarcity in the data set could bring large uncertainties to the Bayesian hierarchical model, causing biases in the result. After meeting the requirements of Standard I, the number of projects in the energy sector, ICT sector, MSW sector, transportation sector, and the W&S sector is 2595, 119, 100, 1462, and 836, respectively. Moreover, the number of contract failure projects in the ICT and MSW sectors is 19 and 0, respectively. That is to say, the percentage of the contract failure projects in these two sectors is 16.0% and 0%. According to the World Bank (2021), a lot of projects in the ICT sector are not recorded, and there are no recorded failed projects in the MSW sector. That is to say, the data in the ICT and MSW sectors could not provide much useful information. Thereafter, only the energy sector, transportation sector, and W&S sector are selected.
- Standard III. Countries that have developed excessive projects in each sector will be excluded, these countries are assumed to have a higher PPP experience level (Marcelo et al. 2017). Fig. 3.4 shows that several countries have developed more PPP projects than others. For example, the number of PPP projects in China, Brazil, and India is more than 2 times that of other countries in the energy sector. To guarantee the robustness of the model, China, Brazil, and India in the energy sector and transportation sector, China in the W&S sector will not be included.

As a result, the maximum experience for the three sectors would be 125, 112, and 122, respectively.

3.4 Research Methods

This section briefs the primary data analysis approaches for the thesis. Detailed research methods for each objective are discussed in later chapters.

3.4.1 Quantitative Analysis

QA is a technique that uses mathematical and statistical modeling, measurement, and research to obtain reliable, valid, and replicable results (Gray and Densten 1998). The result of QA is objective and specific. In contrast to QA, the qualitative analysis uses subjective judgment to analyze the problem based on non-quantifiable information, such as management expertise and experience. However, the main disadvantages of qualitative analysis are subjective, non-quantifiable, and case-specific.

For quantification of developing countries' PPP experience levels, the PPP experience of a country could be measured by the obtained experience levels. To finish this task, the Bayesian hierarchical model and the binary segmentation method have been used. For quantification of countries' importance, the importance of a country in joining a PPP project in foreign countries can be quantified. To finish this task, the SNA method has been adopted. For the prediction of the contract failure of a PPP project, QA can use exact inputs such as project contract period, investment, and countries' experience. These parameters can be fed into the computerized model to yield a correct and objective result, such as the probability of a PPP contract is going to fail. To finish this task, ML methods and correlation analysis have been used.

3.4.2 Stochastic Analysis

In deterministic models, the output of the model is fully determined by the parameter values and the initial conditions. While a stochastic model process has some inherent randomness, the same set of parameter values and initial conditions could lead to an ensemble of different outputs. In the context of quantifying PPP experience levels, the PPP experience for a country is usually measured by the number of PPP projects that have been developed. However, as the number of PPP projects in the current database is not accurate with some minor PPP projects neglected, it is unreasonable

to count only the PPP projects in the database without considering the uncertainty in the number of PPP projects.

3.4.3 Data Analysis Software

The data is analyzed by programming using Python, some common libraries have been used. For example, libraries named matplotlib, seaborn, and Geopandas have been used to visualize the data and findings, pandas, scipy, and NumPy libraries have been used to process the data and do some calculations, the sklearn library has been used to analyze the data, and the Kera library has been used to build the artificial neural network (ANN). Moreover, to build and analyze social networks, the graph database named Neo4j along with a specific language named Cypher, which is a declarative graph query language, has been utilized. These tools have guaranteed that the objectives in this thesis could be achieved precisely and smoothly.

3.5 Summary

To carry out the study systematically and rationally, the research design has been organized based on the objectives of the research. First, the main steps of the research have been listed out. Ten steps will be followed to achieve the objectives, which contain several specific tasks, of this research. Second, the data sources, data collection method, and data preprocessing process have been introduced. The data sets used are from the public databases from the World Bank, and they have been cleaned to make the data appropriate to be analyzed. Third, the data analysis methods have been discussed. This research adopts the quantitative method, primary analysis methods corresponding to each task have been introduced. Finally, the data analysis software and tools have been given. The research has been carried out mainly using the Python language.

Chapter 4 Quantification of Countries' PPP Experience Levels

4.1 Introduction

Learning from experience to improve future infrastructure PPPs has attracted a lot of attention. For instance, Sampson (2005) found that institutional capabilities and performance can be strengthened by the experience. Jones and Howarth (2012) stated that experience in collaboration over the implementation of infrastructure can contribute to a peaceful and effective solution to interest disputes. O'Shea et al. (2020) pointed out a gradual change in the governance of PPPs in Ireland has been found by studying 27 PPP projects. Cohen et al. (2016) stated that the lessons learned from the Milan metro line project can help in cost reduction in future projects. Hurk (2016) concluded that the government could adjust the contracts to the market as they develop more projects by studying four road projects in Belgium. Overall, it is sure that a country can gain experience from previous PPP projects. Unfortunately, the above-mentioned studies are commonly about the lessons learned from the previous PPP projects. The deep insight about the impact of PPP experience on the PPP performance is, however, absent.

This chapter carries out a detailed study. First, the number of change points in the data set is identified based on the binary segmentation method. Second, the Bayesian hierarchical model is developed to locate the positions of the change points, and different experience levels are divided based on the location of the change points. Third, the advantages of the proposed model are compared with those of the conventional Bayesian hierarchical model. Finally, some suggestions for both public and private sectors have been given based on the findings of the research.

4.2 Background

4.2.1 Binary Segmentation Method

The binary segmentation method starts with the single change point detection based on the mean or variance of the data set, followed by the same process in newly generated segments until all change points are detected.

Given a data set with n data points $\{y_t: t = 1, 2, 3, \dots, n\}$, a point y_τ can be treated as a change point when the variance or mean of the segment $\{y_1, y_2, \dots, y_\tau\}$ is different from that of the segment $\{y_{\tau+1}, y_{\tau+2}, \dots, y_n\}$ (Rohrbeck 2013). Assuming that the number of change points is m , their positions can be denoted by $\{\tau_m: m = 1, 2, 3, \dots, m\}$. As a result, the m change points split the data into $m+1$ segments, and the i th segment contains the points between $y_{(\tau_{i-1}+1)}$ and y_{τ_i} , denoted by $y_{(\tau_{i-1}+1):\tau_i}$. When $i=m+1$, $\tau_{m+1} = n$, which denotes that all points between $y_{(\tau_m+1)}$ and y_n belong to the last segment. However, when $i=1$, $\tau_0 = 0$, which denotes that all points between y_1 and y_{τ_1} belong to the first segment. According to Killick et al. (2012), the basic principle of determining the number of change points is to minimize the value of Eq. (4.1), which denotes the sum of the cost function for each sub-segment and the penalty.

$$F = \sum_{i=1}^{m+1} \left[C(y_{(\tau_{i-1}+1):\tau_i}) \right] + \beta f(m) \quad (4.1)$$

where C is the cost function of a segment, and $\beta f(m)$ is the penalty whose purpose is to avoid the overfitting of the optimizing process.

In general, the cost function C is usually chosen as twice the negative log-likelihood (Chen and Gupta 2011; Horváth 1993). For example, for a sub-segment between s and t , the cost function can be denoted by:

$$C(y_{s:t}) = -2l(\mu, \sigma_s, \dots, \sigma_t | y_s, \dots, y_t) = \sum_{i=s}^t \left[\frac{(y_i - \mu)^2}{\sigma_i^2} + \log(2\pi\sigma_i^2) \right] \quad (4.2)$$

Besides, the item $f(m)$ in the penalty $\beta f(m)$ is usually a linear function of the number of change points m :

$$f(m) = m \quad (4.3)$$

This function has been adopted by several penalties, such as Schwarz Information Criterion (SIC) (Schwarz 1978; Yao 1988), where β in penalty $\beta f(m)$ is determined by:

$$\beta = p \log n \quad (4.4)$$

where n is the size of the data set, and p is the number of additional parameters introduced by adding one additional change point. In this research, the number of the

additional parameters depends on the number of priors and hyper-priors in each segment.

When it comes to the single change-point problem, the general idea is to find a split that makes Eq. (4.1) smaller than the cost function for the whole data set (Rohrbeck 2013). Eq. (4.5) demonstrates the method of detecting a single change point. If there exists a point at τ that satisfies this condition, y_τ is then a change point.

$$C(y_{1:\tau}) + C(y_{(\tau+1):n}) + \beta < C(y_{1:n}) \quad (4.5)$$

If one change point has been detected, the whole data set will be divided into 2 segments, where the single change point method will be iteratively and separately applied to each sub-segment until all change points have been detected.

4.2.2 Bayesian Hierarchical Modeling

A Bayesian hierarchical model starts from an initial guess on the prior distribution $p(\theta)$ by inferring from previous knowledge, experience, or assumptions. Then, the result of Bayesian inference, posterior distribution $p(\theta|y)$, incorporating the experimental knowledge $p(y|\theta)$ can be obtained (Imholz et al. 2020). The Bayesian theorem can be described as below:

$$p(\theta | y) = \frac{p(y | \theta) p(\theta)}{p(y)} \quad (4.6)$$

where θ is the vector of parameters that are described as distributions, y is the vector of observations. $p(\theta)$ is the prior, $p(y|\theta)$ is the likelihood function, and $p(y)$ is the evidence. If the evidence is neglected, the Bayesian theorem can be written in the below form:

$$p(\theta | y) \propto p(y | \theta) \times p(\theta) \quad (4.7)$$

For a Bayesian hierarchical model, more layers with multiple parameters are considered (Yan and Moradkhani 2015). Priors are estimated directly by other priors that are called hyper-priors rather than being fixed to constant numbers. The parameters for these hyper-priors are called hyper-parameters. The use of hyper-priors gives more information to make more accurate beliefs in the behavior of a parameter. The inference process of a Bayesian hierarchical model can be seen from the below equation:

$$p(\theta|y) \propto p(y|\theta) \times p(\theta|\varphi) \times p(\varphi) \quad (4.8)$$

where $p(y|\theta)$ is the likelihood, $p(\theta|\varphi)$ is the prior distribution, and $p(\varphi)$ is the hyper-prior distribution.

4.3 Overview of the Proposed Hybrid Bayesian Model

From the current literature, no general model has been found with uncertainties considered for analyzing experience levels. To quantify the PPP experience levels for developing countries, a novel probabilistic method that combines the binary segmentation method and Bayesian hierarchical model is proposed. First, the number of change points, where the level of experience for a country transforms suddenly, is searched by the binary segmentation method. Besides, the location of the change point is detected through the Bayesian hierarchical model with results from the binary segmentation method being informative priors. Finally, the PPP experience levels are categorized based on the detected change points. The framework of the proposed approach can be found in Fig. 4.1, which incorporates three modules, including 1) PPP experience quantification, 2) change points determination, and 3) Bayesian hierarchical modeling and assessment.

Fig. 4.1. The proposed framework of quantifying PPP experience levels

4.3.1 PPP Experience Quantification

PPP experience means the substantial expertise that is likely to be captured over decades of working on a significant number of similar PPP projects no matter what the outcomes of these projects are (Andrew Fitzpatrick et al. 2014). Therefore, it is

reasonable to assume that the PPP experience varies with the PPP sectors. The PPP experience of a country is defined as the number of PPP projects that it has developed in this chapter. PPP experience needs to be measured before its levels can be classified quantitatively. Although it is sure that the levels of complexity of the PPP projects could also affect the PPP experience of a country, they are not considered in the current research. The reason is that it is difficult to combine the complexity with the number of projects. Therefore, to reduce the uncertainties of the results, the complexity of the project is not considered in this part. However, it is considered in the later chapter where the PPP contract failure prediction is carried out. Table 4-1 includes an example of how to calculate the PPP experience for a country. “Project experience” is the PPP experience of a country when it develops the project.

Table 4-1 An example of the projects developed by three countries

Country	Project	Year 1		Year 2	Year 3
Country A	Project name	P1	P2	P3	P4
	Project experience	1	2	3	4
Country B	Project name	-	-	P5	P6
	Project experience	-	-	1	2
Country C	Project name	-	-	-	P7
	Project experience	-	-	-	1

Table 4-1 shows that the number of PPP projects for “Country A” in Year 1, Year 2, and Year 3 is 2, 1, and 1, respectively. Therefore, from Year 1 to Year 3, the PPP experience for “Country A” is 4. Based on the same method, the PPP experience for “Country B” and “Country C” can be calculated as 2 and 1, respectively. From a global perspective, the number of projects finished at experience j is N_j , which is the sum of projects finished at experience j in different countries. For example, N_1 and N_2 for the projects in Table 4-1 are 3 and 2, respectively.

As previously mentioned, gaining in PPP experience would reduce the contract failure rate r_j , which is the proportion of the number of contract failure projects to that of all PPP projects (Junqueira and Pmp 2016), as calculated by Eq. (4.9). Although r_j may be influenced by other factors, this research mainly focuses on the PPP experience. To reduce the error for the inference process, r_j is multiplied by 100. If an abrupt change, where the variance of data makes a significant jump, in r_j appears at a specific experience point, it is called a change point. A series of change points

separate the data set into continuous segments. It is assumed that the value of the parameter associated with each segment is independent of the other (Fearnhead 2006). Therefore, the corresponding PPP experience at change points would be the bounds of different experience levels.

$$r_j = \frac{n_1 + \dots + n_j}{N_1 + \dots + N_j} \quad (4.9)$$

where n_j is the number of failed projects at experience j for all countries.

4.3.2 Change Points Determination

The number of change points is first detected by the binary segmentation method, which is a prerequisite for the deployment of their locations by the Bayesian hierarchical model.

The binary segmentation method with the SIC penalty has been adopted to find the number of change points in this research. The convergence of the binary segmentation process is checked by the diagnostic plot whose x -axis is the number of change points and the y -axis is the corresponding variance of the model. The principle is that the improvement in the variance of the model will be significantly large if a true change point is added. What this means is that the difference in the fitting result will not improve a lot after all change points are detected. Therefore, the elbow of the diagnostics plot is chosen as the true number of change points (Lavielle 2005).

4.3.3 Bayesian Hierarchical Modeling and Assessment

The generic structure of the proposed hierarchical model is illustrated in Fig. 4.2, where the known and unknown parameters are denoted as rectangles and ellipses, respectively. The whole data set is split into $m+1$ segments by m change points. Furthermore, each segment has an identical structure and distinct parameter specifications (Wyse et al. 2011). The parameters for each segment and the location of change points are respectively surrounded by a dotted frame and a solid frame. During the Bayesian process, the selection of parameters under different observations can be achieved by a switch function as given by Eq. (4.10).

$$result = switch(condition, result1, result2) \quad (4.10)$$

where the *result* is the output of the function. The *result* equals *result1* if the *condition* is true, or it is *result2*. Besides, *result1* can be other embedded switch functions.

Fig. 4.2. Generic structure of the proposed Bayesian hierarchical model

Three levels are included in the whole model: 1) the first level contains a set of observations y , such as contract failure rate r_j in this context. y is a distribution with parameters θ that is the result of a switch function, where n indicates the size of the data set. The distribution of y , regarding the distribution type and the number of parameters, depends on the properties of the data set. For example, the mean value, variance, and mode value of the data could be used to distinguish one distribution from another. Switch function can pick the value from θ_1 to θ_{m+1} based on the location of the change point θ_{cm} , where the subscript c denotes that the parameter is related to the location of change points, 2) the second level contains priors for each parameter in the first level, such as θ_{cm} and θ_{m+1} . θ_{cm} is assigned a noninformative prior a_{cm} , part of which can be determined from the result of the binary segmentation method in this research. For example, a_{cm} is the bound of the experience level in this research. Noninformative priors mean the general information of a parameter, which will not have a decisive impact on the posterior distribution if enough observations are provided. Unlike θ_{cm} , θ_{m+1} is governed by other hyper-parameter ϕ_{m+1} , and 3) the third level gives the distribution of the hyper-parameter ϕ_{m+1} , which will be decided by a

fixed hyper-prior a_{m+1} . Finally, a_{m+1} can be determined according to the data set and expertise.

A python library PyMC3, whose basic sampling algorithm is Markov Chain Monte Carlo (MCMC), is adopted to achieve the Bayesian analysis in this study. PyMC3 allows users to run the model in parallel and generate a series of chains of the parameters. Each chain is independent of others although the distribution of each chain should be similar. The aim of these chains is not only to check for the convergence of the model but also to increase the sample size (Martin 2016). The model will be applied to different sectors to obtain the PPP experience levels.

4.4 Analysis of Results

The Bayesian hierarchical model has been developed to categorize the PPP experience levels of developing countries in different sectors. In this section, results are presented. First, the resultant number of change points in each sector is determined. Second, the Bayesian hierarchical model is established based on results in the last step. Third, the convergence of the Bayesian hierarchical model is checked and the posterior distribution of the parameter is given. Finally, the levels of the PPP experience are categorized and analyzed.

4.4.1 The Resultant Number of Change Points

Fig. 4.3 gives the diagnostic plot where the red point is the number of change points. Besides, Table 4-2 lists the location of each change point for different sectors.

Fig. 4.3. Diagnostic plot

Table 4-2 Locations of change points by the binary segmentation method

Location point	Energy sector	Transportation sector	W&S sector
c_1	25	12	7
c_2	56	36	52
c_3	-	82	80

Fig. 4.3 shows that the variance improvement at the red point is much larger than that at other places. Therefore, the number of change points for the energy sector, transportation sector, as well as W&S sector is 2, 3, and 3, respectively. These change points split the data set into 3, 4, and 4 segments. When considering the developing countries that are not considered in Standard III, the number of experience levels for the three sectors is 4, 5, and 5, respectively. The location of the change point obtained by the binary segmentation method is denoted by b_m , where m is the number of change points. m and b_m are used as prior information for the Bayesian hierarchical model.

4.4.2 Model for Quantifying PPP Experience Levels

Fig. 4.4 shows a Kruschke diagram for one segment and one change point of the proposed model, where three levels correspond to hierarchies of the Bayesian hierarchy model. Table 4-3 gives a summary of the distribution of each parameter.

Fig. 4.4. The Bayesian hierarchical model for one change point and one segment

Table 4-3 The probability distribution of each parameter

1st level:	$r_j \sim N(\mu, \sigma^2)$
Posterior distribution	$l_{c1} = 0 \ (m = 1), l_{cm} = c_{m-1} \ (m > 1)$ $h_{cm} = n$ (the last change point), $h_{cm} = b_{m+1}$ (other change points)
2nd level:	$c_m \sim \text{Discrete } U(l_{cm}, h_{cm})$
Prior distribution	$\mu_{m+1} \sim U(l_{\mu(m+1)}, h_{\mu(m+1)}), \sigma_{m+1} \sim HN(\sigma_{\sigma(m+1)})$
3rd level:	Energy sector: $l_{\mu(m+1)} = 0, h_{\mu(m+1)} = 10, \sigma_{\sigma(m+1)} = 6$
Hyper-prior distribution	Transportation sector: $l_{\mu(m+1)} = 0, h_{\mu(m+1)} = 16, \sigma_{\sigma(m+1)} = 6$ W&S sector: $l_{\mu(m+1)} = 0, h_{\mu(m+1)} = 18, \sigma_{\sigma(m+1)} = 6$

On the first level, there is a group of observations y . In this research, the observation is the contract failure rate r_j , which is modeled with a normal distribution $r_j \sim N(\mu, \sigma^2)$. Two sets of switch functions are used to select the correct parameters for both of μ and σ from μ_1 to μ_{m+1} and σ_1 to σ_{m+1} , respectively. The number of switch functions in each group is determined based on the number of change points obtained by the binary segmentation method.

On the second level, prior μ_{m+1} and σ_{m+1} are described as the function of other hyper-parameters. μ_{m+1} is modeled as a uniform distribution with the lower bound of $l_{\mu(m+1)}$ and an upper bound of $h_{\mu(m+1)}$, where the subscript μ indicates the parameters for $p(\mu_{m+1})$. After trying various common probability distributions for a variance, such as a half-normal distribution and an inverse-gamma distribution (Gelman 2006), σ_{m+1} is modeled using a half-normal distribution with a variance $\sigma_{\sigma(m+1)}$, where the subscript σ indicates the parameters for $p(\sigma_{m+1})$. The model using the half-normal distribution is easier to converge than others in this context.

On the third level, hyper-priors are defined as fixed values based on results from the last section. First, $l_{\mu(m+1)}$ and $h_{\mu(m+1)}$ denote the lower and upper bounds of the contract failure rate in each segment, respectively. As the minimum contract failure rate is always larger than 0, $l_{\mu(m+1)}$ is therefore 0. $h_{\mu(m+1)}$ should be less than the maximum contract failure rate in each sector. As a result, $h_{\mu(m+1)}$ for three sectors is 10, 16, and 18, respectively. Second, the location of the change point c_m is determined by a discrete uniform distribution with the bounding of l_{cm} and h_{cm} because the experience is an integer in this study. As the experience of the first change point c_1 cannot be negative, the l_{c1} is 0. For remaining change points, l_{cm} of the change point c_m equals the location of its previous change point c_{m-1} because the experience at a change point

should be larger than that of its previous one. For the last change point, h_{cm} is n , which is the number of points in the data set. However, the value of a change point cannot be larger than that of its later one. Therefore, h_{cm} for the remaining change points is the location of their later change point c_m . In this research, the locations obtained by the binary segmentation method is used as informative priors to lower the uncertainty. More specifically, $h_{cm} = b_{m+1}$. For example, $h_{c1} = b_2 = 56$ for the energy sector. Third, $\sigma_{\sigma(m+1)}$ is 6 in this research, it is found that its value has less effect on the results after trying different values.

In total, 3 chains are used to simulate the sampling process in each PPP sector, 4000 samples have been drawn with 2100 first samples discarded to eliminate the effect by randomness in the selected starting point in each MCMC chain (Hamra et al. 2013).

4.4.3 Convergence of the Bayesian Hierarchical Model

Different parameters exist in the model for different PPP sectors. Table 4-4 gives a summary of the parameters in the model for the transportation sector. Fig. 4.5-Fig. 4.7 demonstrate the posteriors of all parameters in different chains denoted by different colors for the transportation sector. Table 4-5 gives the result of the Gelman-Rubin test for different sectors.

Table 4-4 lists 11 unknown parameters and 18 known parameters for the transportation sector. Besides, the total number of unknown and known parameters for three PPP sectors is 30 and 49, respectively.

Table 4-4 Parameters in the proposed model for the transportation sector

Segment	Prior	Hyper-prior
Segment 1	c_1, μ_1, σ_1	$l_{c1}, h_{c1}, l_{\mu1}, h_{\mu1}, \sigma_{\sigma1}$
Segment 2	c_2, μ_2, σ_2	$l_{c2}, h_{c2}, l_{\mu2}, h_{\mu2}, \sigma_{\sigma2}$
Segment 3	c_3, μ_3, σ_3	$l_{c3}, h_{c3}, l_{\mu3}, h_{\mu3}, \sigma_{\sigma3}$
Segment 4	μ_4, σ_4	$l_{\mu4}, h_{\mu4}, \sigma_{\sigma4}$

The convergence of the model needs to be checked before the results can be shown. The first method to verify the convergence of the model is the kernel density estimate (KDE) plot. From Fig. 4.5 to Fig. 4.7, the left side is the KDE and the right side is the samples of the Markov chain plotted in sequential order. For a convergent model, KDE plots of parameters should resemble smooth curves, while the sampled value

for each parameter should look like white noise, and no recognizable pattern should be detected. From this perspective, good convergence has been achieved in the model.

Fig. 4.5. Posterior densities of the prior c_1 - c_3 under different chains for the transportation sector

Fig. 4.6. Posterior densities of the prior μ_1 - μ_4 under different chains for the transportation sector

Fig. 4.7. Posterior densities of the prior σ_1 - σ_4 under different chains for the transportation sector

The second method to check for the convergence of the MCMC result is the Gelman-Rubin test, this quantitative method compares the variance among different chains with the pooled variance (Somogyvári and Reich 2019). This type of test applies to all those situations where inferences are summarized by posterior means and variances. The output of this test is the potential scale reduction factor R , which is expected to be in the vicinity of 1.0 if a model is convergent. A large R means more simulations or samples are needed to decrease the variance of the model (Brooks and Gelman 1998). It can be seen from Table 4-5 that R values for all parameters are close to 1.0, meaning that the convergence of the model can be guaranteed.

Table 4-5 R value of c , μ , and σ for different segments in different sectors

Variable	c_1	c_2	c_3	μ_1	μ_2	μ_3	μ_4	σ_1	σ_2	σ_3	σ_4
Energy	1.002	1.002	-	1.0	1.0	1.01	-	0.9999	1.001	1.0	-
Transportation	1.002	1.002	1.016	1.0	1.001	1.01	1.009	1.0	1.002	1.005	1.01
W&S	1.002	1.007	1.006	1.0	1.002	1.005	1.004	0.9999	1.003	1.002	1.003

4.4.4 Posterior Probability of Parameters

The posterior probability of a parameter is the probability of an event after taking into account the data information. 95% highest posterior density (HPD) interval is adopted to visualize and quantify the uncertainties in the data set. HPD interval means that

every point within it has a higher probability than points out of this region (Turkkan and Pham-Gia 1993). “95% HPD” denotes that the posterior probability of the parameter lies in the interval is 95%. Fig. 4.8-Fig. 4.10 display the posterior distribution of change points c_1 - c_3 , prior μ_1 - μ_4 , and σ_1 - σ_4 with 95% HPD for the transportation sector. Table 4-6 lists a summary of the mean value of different parameters for different sectors.

Fig. 4.8. Posterior distribution of the prior c_1 - c_3 for the transportation sector

Fig. 4.9. Posterior distribution of the prior μ_1 - μ_4 for the transportation sector

Fig. 4.10. Posterior distribution of the prior σ_1 - σ_4 for the transportation sector

Table 4-6 Mean value for c , μ , and σ in different sectors

Sector	c_1	c_2	c_3	μ_1	μ_2	μ_3	μ_4	σ_1	σ_2	σ_3	σ_4
Energy	30	57	-	6.5	4.7	4.4	-	1.2	0.13	0.046	-
Transportation	13	39	80	14.0	12.0	10.0	9.2	1.2	0.23	0.39	0.3
W&S	13	45	85	15.0	17.0	14.0	12.0	1.5	0.91	0.66	0.49

The experience needed for a developing country to rise to a higher experience level varies with each sector. For the energy sector, Table 4-6 shows that fewer projects are needed to increase the PPP experience level from level 2 to level 3 than in other sectors. However, more projects are needed to transform into level 2, which is more than twice the experience for others. This indicates that more experience in the energy sector is needed to improve the performance of PPP projects in the beginning but considerable progress is likely to be made as more projects are initiated. For the transportation sector, fewer projects are needed to gain enough experience because the difference between the bounds of experience levels is fewer.

There are larger uncertainties in the bounds for higher experience levels. As shown in Fig. 4.8, the mean value of change points for the transportation sector is 13, 39, and 80, respectively, with the 95% HPD of 11-13 times, 36-41 times, and 74-86 times. The corresponding 95% HPD for 2 change points in the energy sector is 28-32 times and 56-58 times, and for 3 change points in the W&S sector is 9-15 times, 40-48 times, and 78-92 times. These results show that the uncertainties in the location of change points are increasing as experience gains. This is caused by data scarcity as fewer and fewer countries appear at a high experience level.

Contract failure rate and decline in the contract failure rate between different experience levels vary with PPP sectors. It can be seen from Table 4-6 that the lowest and largest contract failure rates appear in the energy sector and W&S sector, respectively. The corresponding average value is 5.2% and 14.5%. That is to say, energy projects are less complex, while W&S projects are more complicated. Therefore, when developing a treatment plant and water utility infrastructure, more attention and manpower are preferred. Moreover, Fig. 4.9 presents that there is a declining tendency for contract failure rate as more projects are developed. From the first experience level to the last one, the improvement in the contract failure rate for the energy sector, transportation sector, and W&S sector is 32.3%, 34.3%, and 20%,

respectively. However, unlike other sectors, growth in contract failure rate has been detected from level 1 (15.0%) to level 2 (17.0%) for the W&S sector. In other words, the performance of projects in this sector may be better in the first several projects.

4.5 PPP Experience Levels of Developing Countries

According to the quantified PPP experience levels, private investors could have a higher opportunity to choose the right country to invest in. It is also a good indicator of how to choose collaborators, for example, if a company is from a country with a high experience level in a specific sector, it has a high probability to be a good partner who has the necessary knowledge and experience in managing a PPP project. Although many factors can affect the partner selection process, the indexes proposed in this chapter should be a good reference especially when less information about a partner is available. Fig. 4.11 demonstrates the different levels of PPP experience for different sectors, where the green dot denotes the contract failure rate under different PPP experiences. The purple dash line is the average contract failure rate in different segments. Besides, the bounds of PPP experience levels are denoted by the yellow lines with the uncertainty filled with gray color. Table 4-7-Table 4-9 summarize one hundred and seventeen countries' experience levels for different sectors. Fig. 4.12 visualizes the distribution of these experience levels, where different color in the map denotes different levels of PPP experience in the transportation sector, the size and color of the dot represent the PPP experience levels of the energy sector along with the W&S sector, respectively. The deeper the color of the map or dot, the higher the level of experience in the transportation sector or W&S sector, the larger the size of the dot, the higher the level of experience in the energy sector. Some conclusions can be obtained.

Fig. 4.11. Bounds of PPP experience levels for different sectors

The learning rate varies with each sector, and a decreasing trend from level to level is observed. Besides, the largest learning rate exists in the first several projects. Fig. 4.11 (a) shows the result for the energy sector, which shows an explicit decrease in the contract failure rate from level 1 to level 2. As experience gains, the effect of learning will decrease as the reduction in the contract failure rate is smaller and smaller. Fig. 4.11 (b) shows the result of the transportation sector. Although the decreasing tendency in the contract failure rate is also detected, the reduction in the learning rate is not obvious. That is to say, potential improvement in project performance is expected to be achieved as more projects in the transportation sector are developed. By comparing the contract failure rate for three sectors, it can be concluded that countries' ability would have a dramatic increase in their first several projects with contract failure rate decreases largely, indicating a higher learning rate.

Table 4-7 PPP experience levels for the energy sector

Level	Experience	Country
1	[0, 30)	'Afghanistan', 'Albania', 'Algeria', 'Angola', 'Armenia', 'Azerbaijan', 'Belarus', 'Belize', 'Bhutan', 'Bolivia', 'Bosnia and Herzegovina', 'Botswana', 'Burkina Faso', 'Cambodia', 'Cameroon', 'Cape Verde', 'Chad', 'Colombia', 'Comoros', 'Congo, Rep.', 'Costa Rica', 'Cuba', 'Côte d'Ivoire', 'Dominican Republic', 'Ecuador', 'Egypt, Arab Rep.', 'El Salvador', 'Ethiopia', 'Fiji', 'Gabon', 'Gambia, The', 'Georgia', 'Ghana', 'Guatemala', 'Guinea', 'Guinea-Bissau', 'Haiti', 'Honduras', 'Iran, Islamic Rep.', 'Iraq', 'Jamaica', 'Jordan', 'Kazakhstan', 'Kenya', 'Kosovo', 'Lao PDR', 'Lesotho', 'Liberia', 'Macedonia, FYR', 'Madagascar', 'Malawi', 'Mauritius', 'Mongolia', 'Morocco', 'Mozambique', 'Myanmar', 'Namibia', 'Nepal', 'Nicaragua', 'Nigeria', 'Papua New Guinea', 'Romania', 'Russian Federation', 'Rwanda', 'Senegal', 'Serbia', 'Sierra Leone', 'Solomon Islands', 'São Tomé and Príncipe', 'Tajikistan', 'Tanzania', 'Timor-Leste', 'Togo', 'Tonga', 'Tunisia', 'Uganda', 'Ukraine', 'Vanuatu', 'Venezuela, RB', 'West Bank and Gaza', 'Yemen, Rep.', 'Zambia'
2	[30, 57)	'Bangladesh', 'Bulgaria', 'Indonesia', 'Malaysia', 'Peru', 'South Africa'
3	[57, 125)	'Argentina', 'Mexico', 'Pakistan', 'Philippines', 'Sri Lanka', 'Thailand', 'Turkey', 'Vietnam'
4	[125,)	'Brazil', 'China', 'India'

Table 4-8 PPP experience levels for the transportation sector

Level	Experience	Country
1	[0, 13)	'Albania', 'Algeria', 'Angola', 'Armenia', 'Bangladesh', 'Benin', 'Bolivia', 'Bulgaria', 'Cambodia', 'Cameroon', 'Comoros', 'Congo, Dem. Rep.', 'Congo, Rep.', 'Costa Rica', 'Cuba', 'Côte d'Ivoire', 'Djibouti', 'Dominican Republic', 'Ecuador', 'Egypt, Arab Rep.', 'Gabon', 'Georgia', 'Ghana', 'Guatemala', 'Guinea', 'Honduras', 'Iraq', 'Jamaica', 'Jordan', 'Kazakhstan', 'Kenya', 'Kosovo', 'Lao PDR', 'Lebanon', 'Liberia', 'Macedonia, FYR', 'Madagascar', 'Malawi', 'Maldives', 'Mali', 'Mauritius', 'Moldova', 'Morocco', 'Mozambique', 'Myanmar', 'Nicaragua', 'Pakistan', 'Paraguay', 'Romania', 'Russian Federation', 'Senegal', 'Sierra Leone', 'Somalia', 'South Africa', 'Sri Lanka', 'Sudan', 'Syrian Arab Republic', 'Tanzania', 'Togo', 'Tunisia', 'Ukraine', 'Venezuela, RB', 'Vietnam', 'Yemen, Rep.', 'Zambia', 'Zimbabwe'
2	[13, 39)	'Indonesia', 'Nigeria', 'Peru', 'Philippines', 'Thailand', 'Turkey'
3	[39, 80)	'Colombia', 'Malaysia'
4	[80, 112)	'Argentina', 'Mexico'
5	[112,)	'Brazil', 'China', 'India'

Table 4-9 PPP experience levels for the W&S sector

Level	Experience	Country
1	[0, 13)	'Albania', 'Armenia', 'Azerbaijan', 'Bolivia', 'Bulgaria', 'Cameroon', 'Central African Republic', 'Congo, Rep.', 'Cuba', 'Côte d'Ivoire', 'Ecuador', 'Egypt, Arab Rep.', 'Gabon', 'Gambia, The', 'Ghana', 'Guatemala', 'Guyana, CR', 'Haiti', 'Honduras', 'Indonesia', 'Jordan', 'Kenya', 'Kosovo', 'Kyrgyz Republic', 'Lebanon', 'Mauritius', 'Montenegro', 'Mozambique', 'Namibia', 'Nepal', 'Niger', 'Papua New Guinea', 'Peru', 'Philippines', 'Romania', 'Senegal', 'Serbia', 'South Africa', 'Sudan', 'Tanzania', 'Tunisia', 'Turkey', 'Uganda', 'Ukraine', 'Uzbekistan', 'Venezuela, RB', 'Vietnam', 'West Bank and Gaza', 'Zambia'
2	[13, 45)	'Algeria', 'Argentina', 'India', 'Malaysia', 'Russian Federation', 'Thailand'
3	[45, 85)	'Colombia', 'Mexico'
4	[85, 122)	'Brazil'
5	[122,)	'China'

Fig. 4.12. Distribution of PPP experience levels around the world

Most of the developing countries do not have enough experience to handle PPP projects. Moreover, the PPP experience levels are not evenly distributed on earth. For the energy sector, Table 4-7 shows that the number of countries in each level is 82, 6, 8, and 3, respectively. Fig. 4.12 displays that countries in the EAP region have higher PPP experience than those in other regions, such as China, Vietnam, and the Philippines. More than 36.4% of the countries with high energy project experience (level 3 or level 4) are distributed in this region, followed by the SA and LAC regions that account for the same value of 27.3%, such as Pakistan, India, and Argentina. However, energy projects are not well developed in SSF and MENA regions with a particularly low experience level (level 1), such as Niger, Egypt, and Sudan. For the transportation sector, Fig. 4.12 shows that the number of countries in each level is 66, 6, 2, 2, and 3, respectively. The high-level PPP experience is mainly discovered in the LAC region, where the number of countries with experience that is higher than level 3 accounts for 57.1% of all countries. However, other regions rank poorly in experience levels, especially MENA and SSF regions. For example, almost all countries in the SSF region have a level 1 transportation experience. This conclusion coincides with the findings in the literature (Loxley 2013). For the W&S sector, Table 4-9 shows that the number of countries at different levels is 48, 6, 2, 1, and 1, respectively. Fig. 4.12 displays that high-level experience is much easier to be found in the LAC and EAP regions. Similar to the transportation sector, limited experience has been detected in the SSF region although the rapid growth in African countries' infrastructure needs has been widely agreed upon. It is, therefore, necessary and

reasonable for these countries to get more support from PPP supporters to promote economic development, such as Multilateral Development Banks (MDBs).

The same country may have different levels of PPP experience in different sectors. Some countries have extensive experience levels in all three sectors, such as China, Brazil, and Mexico. Although India has a high experience level in the energy and transportation sector, it is suffering from a lack of experience in the W&S sector with an experience level of 2. This conclusion is in line with the conclusion from the other study by Wu et al. (2016). The same phenomenon is also found in other countries, such as Argentina. Besides, the PPP experience level of some countries in the MENA region is low in almost every sector, such as Iran, Iraq, and Afghanistan. These countries have developed fewer PPP projects because of the sectarian conflict, and economic uncertainty, which has impeded the inflow of foreign direct investment (FDI). This conclusion is the same as the one from Investment Security in the Mediterranean (ISMED) that emphasizes the need for higher experience levels in part of the MENA region (Andrew Fitzpatrick et al. 2014). Thereafter, when competing with other regions for more private investment to improve the living standards, more actions have to be taken to reduce the risks bore by private sectors.

4.6 Comparison of Conventional and Hybrid Bayesian Models

A comparison between the proposed method and the conventional one is conducted to further demonstrate the advantages of the proposed methodology based on the data from the transportation sector. Table 4-10 lists the prior distributions and results of the change point by the Bayesian hierarchical model with and without informative priors. Fig. 4.13 gives the posterior distribution of c_1 - c_3 under noninformative priors.

Table 4-10 Comparison of models with informative and noninformative priors

Change point	Model with informative priors			Model with noninformative priors		
	Prior distribution	Result		Prior distribution	Result	
		Mean	95% HPD		Mean	95% HPD
c_1	(0, 36)	13	(11, 13)	(0, 112)	40	(38, 43)
c_2	(c_1 , 80)	39	(36, 41)	(c_1 , 112)	61	(59, 63)
c_3	(c_2 , 112)	80	(74, 86)	(c_2 , 112)	85	(81, 90)

Fig. 4.13. Posterior distribution of c_1 - c_3 for the transportation sector under noninformative priors

As previously mentioned, the arbitrary selection of the number of change points may cause errors in detecting their locations. The first advantage of the proposed hybrid model is that the number of change points can be obtained from the binary segmentation method. By referring to the number of change points, the switch function can be added to set the parameters for the Bayesian hierarchical model in different segments. When compared with conventional methods that often assume or adopt complicated algorithms to determine the number of change points, the proposed method can determine the number of change points more precisely with less computational complexity. The second advantage is that the location of the change point from the binary segmentation method is the informative prior for the Bayesian hierarchical model in the new proposed methodology, which can contribute to a more precise prediction.

In the model with informative priors, the upper bound of the probability distribution of each change point is determined according to the results of the binary segmentation method. As shown in Table 4-10, the three upper bounds are 36, 80, and 112, respectively. Unlike the model with informative priors, the noninformative priors have to be adopted in the model with noninformative priors. As the approximate locations of the change point are not available based on prior knowledge, the upper bound of each change point distribution should be the number of observations in the data set, which is 112 for the transportation sector, to guarantee that all possible change points can be picked.

Table 4-10 shows that the change point at 39 detected by the proposed method is similar to the one at 40 found by the model using noninformative priors. However,

the other two change points of the two models are different, especially the one at 13. Fig. 4.11 (b) shows that there is an obvious platform between the experience 15 and 38 after a sharp drop in the contract failure rate in the transportation sector. Therefore, there should be a change point near experience 15. It can be seen from Table 4-10 that the newly proposed method has detected the location of the change point c_1 , the mean of which is 13, while the other model has failed to detect it. Besides, the model with noninformative priors has detected another change point between 59 and 63, which, however, does not contain an abrupt change in the contract failure rate according to Fig. 4.11 (b). The results indicate that the model may detect some less important change points while neglecting some critical ones when using noninformative priors, which may introduce the deviation to the decision-making process. In other words, the proposed methodology outperforms the conventional one in detecting change points.

4.7 Summary

PPP experience is one of the most important advantages for public agencies to deal with the relationship with the private counterparty. However, most private investors only have a qualitative understanding of the PPP experience of a country. The objective of this chapter is to quantify the levels of countries' PPP experience for different PPP sectors in a data-driven manner, which is expected to provide a guideline for private investment. Besides, the obtained PPP experience levels could be treated as the new factors for PPP contract failure prediction. In this research, the definition of PPP experience is conceptualized and data exploration is conducted to clean and select data from the World Bank's PPI database. According to the results, PPP experience levels for the energy sector, transportation sector, and water & sewerage sector are 4, 5, and 5, respectively. Besides, the PPP experience level is not evenly distributed around the world, for example, EAP and LAC regions have a higher experience level than other regions. The same trend has been detected at a country level. For example, India has a higher experience level in the transportation and energy sector than in the water & sewerage sector.

The proposed methodology has shown good performance in detecting the number and locations of change points with the data uncertainty considered. In the developed

model, the number of change points is detected using the binary segmentation method, and the position of each change point is determined by the Bayesian hierarchical model. The primary points are shown as follows:

1. A hybrid methodology is proposed for change point detection based on the binary segmentation method, the Bayesian hierarchical model, and the switch function. The number of change points obtained from the binary segmentation method can be used to set the number of switch functions that can determine the parameters of the Bayesian hierarchical model in different segments.
2. The locations of change points obtained from the binary segmentation method can be used as informative priors for the Bayesian hierarchical model. In this manner, the uncertainty in the data set can be taken into account.
3. The developed method has been used to quantify countries' PPP experience levels in different sectors, and it can detect more critical change points when compared with the model using noninformative priors. Moreover, it is simple to implement and can also be used in other domains and practical problems that detect the change point in the data set.
4. The learning rate is different for each sector. Gaining experience in the transportation sector is easier than others as the distance between bounds for each level is less.
5. Some countries have low experience levels in all three sectors, such as Iran. Moreover, the water & sewerage sector has a higher contract failure rate than other sectors, more preparations should be given when initiating PPP projects in this sector.

Inexperienced governments may bring a series of problems to the PPP procurement process, for example, a low-level experience country may make tender documents sophisticated with detailed specifications, thereby impeding the innovation of private sectors regarding technology and management. Furthermore, the lack of relevant PPP experience would bring high risk to private investors due to the overpromise by the governments, decertifying the project from consideration (Sachs et al. 2007). Based on the results of this research, some guidelines are given for both private investors and public agencies.

From the perspective of private investors, private investors could catch the appropriate opportunities by referring to the results in this chapter. For example, when investing in energy projects, countries in the EAP region should be the first option, such as China, Vietnam, and Philippines. However, when investing in transportation projects, the LAC region should have a better environment, such as Argentina, Mexico, and Brazil. Although more experience means a lower contract failure rate in the energy and transportation sector, it is not the case for the water & sewerage sector. Thereafter, when investing water & sewerage sector, it is wise to avoid investment in countries with experience between 15 and 48 which has the highest risk of contract failure. As the track of making PPP projects successful is an important forecaster of future success, a private company from a country with a high experience level should be a good collaborator (Andrew Fitzpatrick et al. 2014).

From the perspective of public agencies, technical and professional training should be implemented to make the governments equipped with the capacity to achieve a sound PPP structure, prepare a contract, and take public responsibility. The governments with low-level experience could learn valuable experience from the leading countries in the same region, such as policy and regulation. Besides, to attract more private investors, public agencies in low-experience countries should strengthen their ability in other aspects, such as the legal framework. Moreover, it is wise for these governments to involve international consultants aiming at a particular type of project.

Chapter 5 Quantification of Countries' Importance in PPP Knowledge Transfer

5.1 Introduction

This chapter intends to provide a deeper understanding of the dynamics embedded in international PPP knowledge transfer. More specifically, the evolution of the role of different countries in transferring PPP knowledge and their relationships would be unpacked. The main objective of this chapter is to analyze the structure of the PPP knowledge transfer network and find influential social actors from 1990 to 2019 by SNA. By adopting the real-world database, the PPP knowledge transfer among different countries has been represented by a series of networks. The characteristics of the network, such as the network density and importance of the nodes have been obtained. The research contributes to construction management by enriching the research on global knowledge transfer in PPP domains. The research also provides practical guidance for correct partner selection by using SNA metrics, which can be used to strengthen the competitiveness of a project team.

This chapter carries out a detailed study. First, the data set is processed to extract useful information for establishing social networks. Second, the social network for each year is built in the Neo4j platform. Third, the networks are analyzed from the views of both the macro-and micro-level metrics in the context of PPP knowledge transfer. Fourth, the movement of countries' importance in transferring PPP knowledge in various sectors is studied.

5.2 Methodology

Knowledge transfer is important for enhancing the capability of the project team in PPP projects. In the pursuit of a better understanding of the evolution of the PPP knowledge transfer around the world, SNA is adopted to analyze the knowledge transfer based on network theory. This section gives a detailed introduction of the proposed method, as shown in Fig. 5.1. The whole workflow includes three primary modules: (i) network data, (ii) network development, and (iii) network analysis.

Fig. 5.1. The framework of studying PPP knowledge transfer

5.2.1 Network Data

External knowledge acquisition can be achieved through a series of interactions, such as alliances, foreign direct investment, acquisitions, mergers, and technology transfer (Kwawu et al. 2010; O’Hagan and Green 2004; Sun et al. 2019). In this research, the projects that involve foreign countries have been named the projects with foreign participation. Based on the literature review, four assumptions are made:

- Assumption 1: Although knowledge transfer is bidirectional, PPP knowledge is assumed to flow from knowledgeable countries that have a high knowledge level, to less-knowledgeable ones with low knowledge levels. In this research, a knowledgeable country is the headquarters of a foreign company in a PPP project, and it can be a developed country or a developing country. A less-knowledgeable country corresponds to the host country of a PPP project in the developing country, which usually has low PPP knowledge level than a developed country (Kang et al. 2019). This assumption is supported by other studies that have provided theoretical evidence that the knowledge transfer direction could be only from the knowledgeable team member to the less-knowledgeable one from a micro and specific perspective (Wang et al. 2019), and the dominant direction of knowledge transfer is from the headquarters in developed countries to its overseas subsidiaries in developing countries when expatriates are assigned due to the organizational ethnocentrism (Przytuła et al. 2018; Tsang 1999).
- Assumption 2: The knowledge of a subsidiary company is mainly from its parent company (Crespo et al. 2020).
- Assumption 3: The role of a foreign partner can be a sponsor, a contractor, a legal advisor, a financial advisor, and an equipment provider in a project team.
- Assumption 4: Although knowledge can be transferred under different relationships corresponding to different roles, only one link between any two

countries will be kept when conducting SNA. The weight of this link would be the sum of the weight in all original links for different roles. The reason is that this research has not considered different knowledge transfer mechanisms and the weight of a link depends on the number of times that the two countries have collaborated in the same year.

PPI database is used to build PPP knowledge transfer networks. Table 5-1 introduces the 4 types of required information in this research: project year, host country, foreign country, and role. Table 5-2 gives an example of one recorded PPP project to exemplify how to obtain foreign countries and their roles from the “Description” variable.

Table 5-1 Introduction of the required information

Information	Introduction	Source
Project year	The year of the project that has been developed.	Obtain from the “IY” variable in the PPI database directly.
Host country	The name of the low- or middle-income country in which the project is based.	Obtain from the “Country” variable in the PPI database directly.
Foreign country	The headquarters of a foreign company in a project with foreign participation.	Extract from the “Description” variable in the PPI database.
Role	The role of a foreign company.	Extract from the “Description” variable in the PPI database.

Table 5-2 A PPP project in the PPI database and part of its variables

IY	Country	Description
2017	Thailand	<p>The project entails the construction, operation, and maintenance of an 8.63 MW industrial-waste-to-energy power plant, located in Hemaraj Chonburi Industrial Estate in Chonburi. Chonburi Clean Energy (CCE), a joint venture company established by SUEZ, WHA Utilities and Power Plc., and Glow Energy Plc. (a subsidiary of ENGIE), is sponsoring the project.</p> <p>Marubeni will provide engineering, procurement, and construction (EPC) services with JFE Engineering of Japan selected as the technology provider with their stoker-type incineration technology.</p>

Three steps are needed:

- 1) Based on Assumption 3, obtain foreign companies and their roles in each project. For example, the foreign sponsors of the project in Table 5-2 are “SUEZ” and “Glow Energy Plc.”, the contractor is “Marubeni”, and the equipment provider is “JFE Engineering of Japan”.
- 2) Based on Assumption 2, find the parent company of the foreign company in the last step. For example, “Glow Energy Plc.” is the subsidiary of “ENGIE”.
- 3) Based on Assumption 1, search headquarters of foreign companies online. For example, the headquarters of “SUEZ” and “ENGIE” are in France, and the headquarters of “Marubeni” and “JFE Engineering of Japan” are in Japan.

As a result, the foreign countries and their roles in the project in Table 5-2 are “Japan (contractor)”, “France (sponsor)”, and “Japan (equipment provider)”.

The data extraction process contains several iterative procedures. First, the author goes through the whole PPI database and makes a good understanding of the structure of the database as well as the exact meaning of different fields. Second, the author begins to extract the information manually according to the above-mentioned steps because the data is unstructured. Third, the author compares the extracted information several times to reduce errors.

5.2.2 Network Development

A social network can be directed or undirected. An undirected network means that the relationship between two nodes is bidirectional. In contrast, a directed network denotes that information can only flow along the direction of the links. Based on Assumption 1, the networks in this research are directed networks.

Based on the obtained information from the last section, a PPP knowledge transfer network for different years is developed. The identity of the country node is “Country” with the property “Name” to store the country name. The relationship between different nodes is defined as “JOIN” which has two properties “Role” and “Number”. “Number” is the number of projects in a country participated by another country as the same role, which is the weight of the edge. Therefore, each edge in the network represents the knowledge transfer path from one country to another as the same role. The arrow of the edge denotes the direction of the knowledge transfer.

Table 5-3 gives 6 imaginary projects to demonstrate how to map the extracted information into a PPP knowledge transfer network. “S/N” is the identity of the projects that locate in countries A, B, and E, respectively. “Description” column includes 5 various companies, where company 1 and company 2 are from country B, company 3 and company 4 come from country C, and company 5 is based in country D. The domain model for these 6 PPP projects has been shown in Fig. 5.2 (a) to give a clearer view of the PPP knowledge transfer network for 2000. It is notable that although company 1 from country B is also involved in project 4 hosted by country B, this relationship will not be taken into consideration as country B is not a foreign country. Besides, according to Assumption 4, the final network for SNA is the one in Fig. 5.2 (b).

Table 5-3 Six imaginary PPP projects for the year 2000

S/N	Project year	Host country	Description	Foreign country (role)
1	2000	A	Company 3: sponsor; Company 5: contractor	C (sponsor); D (contractor)
2	2000	A	Company 1: legal advisor; Company 5: contractor	B (legal advisor); D (contractor)
3	2000	B	Company 4: contractor; Company 5: equipment provider	C (contractor); D (equipment provider)
4	2000	B	Company 1: sponsor; Company 5: sponsor	B (sponsor); D (sponsor)
5	2000	E	Company 5: sponsor	D (sponsor)
6	2000	E	Company 3: sponsor; Company 2: contractor	B (contractor); D (sponsor)

Fig. 5.2. The structure of the PPP knowledge transfer network for the year 2000

The network will be built based on the Neo4j platform. Social networks in the Neo4j can be queried by Cypher language. Cypher can be executed by Python language that contains several useful libraries, such as pandas and NumPy. The combination of Python and Neo4j will ease the process of building and analyzing the network.

5.3 Network Analysis

Based on the developed PPP knowledge transfer networks, the properties of the network and dynamic interactions of different countries can be found by calculating the SNA metrics. Although these measurements have been explained from different perspectives in the PPP domain, they do vary a little depending on the context of research (Guevara et al. 2020; Wang et al. 2020). This research would explore and explain the application of these metrics in the PPP knowledge transfer process from both macro and micro perspectives.

5.3.1 Macro-level Metrics

The macro-level metrics are network-based, which allows for the visualization and understanding of PPP knowledge transfer among countries from a holistic view. At this level, the common SNA metrics can be network size including the number of the nodes (N) and relationships (E), average degree (AD), network diameter (ND), and network density (D). Besides, according to whether the replicated link between two nodes is considered or not, network density can be categorized into unweighted density (UD) and weighted density (WD). More indicatively, N and E are the numbers of the countries and relationships involved in the current network, which can be used to measure the extent of international collaboration. AD is the average number of edges between two nodes in the network, which represents the average times a country has been engaged in the PPP project in other countries in the same network. ND is the length of the longest of all shortest paths between any two nodes in a network, which reflects the extent of integration of different countries in the PPP domain. UD and WD are the ratios between the actual number of ties in the network and that of the maximum possible ties in the same network, which illustrates the preference by a country for joining the PPP market in other countries. Detailed calculations of these metrics are given in Eqs. (5.1)-(5.3).

$$AD = \frac{E}{N} \quad (5.1)$$

$$ND = \max d(n_i, n_j) \quad (5.2)$$

$$D = \frac{E}{N(N-1)} \quad (5.3)$$

where $d(n_i, n_j)$ is the shortest distance between node i and node j .

5.3.2 Micro-level Metrics

The micro-level metrics are actor-based, through which the behavior of each country can be obtained. At this level, the employed metrics are degree centrality (CD) and PageRank (PR).

CD counts the number of nodes that a particular node is linked to, and it can be classified as in-degree (ID) centrality and out-degree (OD) centrality. In-degree centrality means the number of ties directed to the node while out-degree centrality is the number of ties that the current node towards others. In the context of PPP knowledge transfer, the CD can be used to identify the knowledge sources or knowledge receivers in a network. A country with a large ID means that it is with large popularity to attract or the willingness to accept the participation from other countries, which acts as the role of a knowledge receiver. At the same time, a large OD denotes that the country is treated as a knowledge source, which is more likely to be knowledgeable, by other countries. A country with both considerable ID and OD centralities is thought of as a knowledge broker, which suggests that the country can transfer knowledge to new countries after they learn from others. The calculation of ID and OD of a node can be achieved by Eq. (5.4) and Eq. (5.5), respectively.

$$ID_i = \sum_{j=1}^N \omega_{ji} \quad (5.4)$$

$$OD_i = \sum_{j=1}^N \omega_{ij} \quad (5.5)$$

where ID_i and OD_i denote the ID and OD for i th node. ω_{ji} denotes the weight of the tie from node j to node i . ω_{ij} denotes the weight of the tie from node i to node j .

PR has been used to rank the relative importance of web pages in a directed network (Wills 2006). Unlike other centrality measures, it is assumed that the importance of a

node does not only rely on the quantity of the ties that link to it, but also on the quality of these links (Balakrishnan and Zhang 2020; Beamer et al. 2017). Fig. 5.3 shows a network with 8 nodes, where the size of the circle represents the *PR* centrality. The *PR* of node B is larger than that of node F despite node F has more links pointing to it, this is because node B is linked with node A that owns a larger *PR*. In other words, the link from node A to B has a high quality. As a result, the latent influence of the node can be found based on *PR*. *PR* has been used in construction projects to detect the most important stakeholders (Nik-Bakht and El-Diraby 2017). In the context of PPP knowledge transfer, the evaluation of the importance of a country should consider the importance of countries pointing to it. Besides, it is important to establish a connection with the country that possesses a large *PR* because the country with a large *PR* may retain a large amount of diverse knowledge due to the decent relationships with knowledgeable countries or the substantial number of links with other countries. The *PR* of a node can be calculated by Eq. (5.6) (Hashemi et al. 2020).

$$PR_i = (1 - d) + d \sum_{j=1}^l \frac{PR_j}{N_j} \quad (5.6)$$

where, PR_i and PR_j are the *PR* for the i th node and j th node, respectively. l is the total number of nodes linking to i th node. N_j is the number of links from the j th node. d is the damping factor, which is 0.85 (Brin and Page 1998). The purpose of the damping factor is to avoid the infinite loop.

Fig. 5.3. *PR* for each node in a network

5.4 Case Study

5.4.1 Descriptive Statistics of the Data

4932 projects have information about the project team, out of which 2231 projects have involved companies from foreign countries. Fig. 5.4 (a) illustrates the dynamics of projects with foreign participation, the total number of PPP projects, and their ratio

over time. Fig. 5.4 (b) gives the distribution of the projects with foreign participation in each country.

There is an obvious rising trend in the number of projects with foreign participation and total PPP projects, while the percentage of projects with foreign participation in the PPP projects decreased after a sharp rising. It can be seen from Fig. 5.4 (a) that the projects with foreign participation reached a peak in 2012 with 182 projects. One of the reasons is that most PPP projects have been developed in 2012, which is 535. However, the percentage of projects with foreign participation in all projects shows a different tendency, which indicates that some developing countries are gradually making progress. The maximum percentage appeared in 1999 reaching 51.2%, and the reason may be that although the demands in PPP projects are dramatically increasing before the 21st century, the PPP knowledge level for most developing countries is too low to carry out the PPP projects without the assistance from countries with rich PPP knowledge. From 2004 on, contrary to the increase in the number of PPP projects, the percentage of projects with foreign participation is gradually declining from 39.2% in 2004 to 26.5% in 2019.

Most developing countries have few opportunities to learn from foreign countries. Fig. 5.4 (b) shows that the probability distribution of projects with foreign participation in each developing country has a long tail with a positive skewness of 4.19, implying the asymmetry in countries' chance to learn from other countries. Furthermore, most countries lie in the range between 0 and 50, where over 10% of the countries have fewer than 10 projects with foreign participation. These countries are still short of enough PPP knowledge when compared with the progress made by other developing countries. The top 5 countries with the most projects with foreign participation are Brazil, China, Mexico, India, and Peru, while the top 5 countries in total PPP projects are China, India, Brazil, Mexico, and Argentina. This shows that different countries may have different policies and knowledge backgrounds when determining whether to bring in foreign partners.

Fig. 5.4. Statistical result of PPP projects with foreign participation

5.4.2 Social Network Development

30 knowledge transfer networks from 1990 to 2019 have been developed. Fig. 5.5 shows an example of the PPP knowledge transfer network for the year 1991, where the circles represent countries, and lines denote the relationship between countries. Based on the developed networks, information can be extracted from the established network by using the Cypher language. For example, the number of the nodes in a network can be queried by “Match (n) Return count(n) as networkSize”, and the name of all engaged foreign countries for China can be queried through “Match (n)-[JOIN]->(m:Country{name: “China”}) Return n.name as foreign_country”.

Fig. 5.5. The PPP knowledge transfer network for the year 1991

5.4.3 Social Network Analysis

The SNA metrics are calculated once the correctness of the networks has been verified in the last section. In this section, the importance of the countries in

knowledge sharing is interpreted based on SNA measurements and the knowledge transfer path is visually shown.

(1) Trends at a Global Level

Macro-level metrics can reflect the dynamics of the network structure from a global perspective, which can be calculated by Eqs. (5.1)-(5.3). Fig. 5.6 depicts the result of macro-level metrics. In the context of PPP knowledge transfer, the result is interpreted as follows.

Fig. 5.6. Evolution of the macro-level metrics of PPP knowledge transfer networks from 1990 to 2019

(1) There is a noticeable trend for international collaboration in the PPP area. It can be found from Fig. 5.6 (a) that the number of nodes is growing, although the percentage of the projects with foreign participation shows a decreasing trend in Fig. 5.4 (a). This could be explained by two reasons: a) developing countries are more likely to involve more foreign countries in the same project together. The average

number of foreign countries in a project has grown from 1 to 1.56 since 1990, and the maximum value is 1.77, and b) more developing countries are involving foreign countries in PPP projects. The number of developing countries that have involved foreign countries has increased from 3 to 33 since 1990, with a peak of 42.

(2) There are more and more interactions among diverse countries. Fig. 5.6 (b) shows a rising tendency in average degree, which suggests that countries are more likely to work with multiple countries in the same year as the average links related to a node are growing. However, the density of the network keeps stable since 2000, as shown in Fig. 5.6 (d). This indicates that the network contains some cliques that are getting denser and denser while the connections between different cliques are sparse, leading to a quicker knowledge transfer process in each clique (Tabassum et al. 2018). However, there is a drop in the average degree after 2012, before which the average degree has boosted. As the number of PPP projects in developing countries is increasing after 2012, the drop in average degree may mainly be explained by the low level of activities across the world due to the challenging economic environment.

(3) The cohesion of the network does not show clear changes. The network cohesion can be measured by the network diameter, and a high diameter indicates low network cohesion (Van den Bos et al. 2018). It can be found from Fig. 5.6 (c) that the diameter of the network is fluctuating between 6 and 9 since 1992. That is to say, the knowledge can be transferred to different countries in the network at a similar speed. The largest diameter, which is 9, in 1997, 1998, 1999, and 2014 suggests that there exist groups of countries that are not working quite closely in these years (Takes and Kusters 2011).

(4) The PPP knowledge transfer network is sparse as the density is near 0. A sparse network will outperform a denser one in recognizing and absorbing new knowledge but is not good at transferring knowledge (Schröpfer et al. 2017). Fig. 5.6 (d) shows that the weighted density is always larger than the unweighted density due to the consideration of the weight of the relationships. The difference between these two measurements is growing, which is more evident during 2011 and 2015. It manifests that a large number of developing countries have built repeated relationships with fixed partners by involving them in domestic PPP projects. That is to say that external companies prefer to participate in projects in countries with which they have

previously collaborated. For example, the number of developing countries that have involved the same foreign country more than 3 times from 2011 to 2015 is 5, 9, 4, 5, and 3, respectively. The maximum number is 9, which appears in 2012. Besides, the number of foreign countries that have been involved in the same developing country more than 3 times from 2011 to 2015 is 6, 6, 3, 3, and 2, respectively. The maximum number is 6, which appears in 2011 and 2012.

Overall, the properties of the networks have been revealed by macro-based metrics. The change in the node size and average degree indicates an international collaboration trend in PPP projects around the world. However, the density of the network does not show an obvious rising tendency, indicating that more effort is needed to achieve PPP globalization. Finally, countries have shown some unique personal behaviors. For instance, they are more likely to cooperate with their previous partners. It is thereby necessary to have a further analysis of the performance of different countries and their interactions.

(2) Trends at a Country Level

Team members can impact the performance and capability of a project team, it is therefore pretty important to choose correct partners with appropriate country backgrounds by understanding their roles in the knowledge transfer process. Fig. 5.7, Fig. 5.8, and Fig. 5.9 illustrate the in-degree, out-degree, and PageRank centrality of the top 3 countries as well as their connected countries where the arrow of the edge is the knowledge transfer orientation. The larger the size of a circle is, the higher the corresponding centrality is. The thickness of the relationship represents the number of projects in which two countries joined at the same time. Besides, the countries whose in-degree and out-degree centralities are larger than 0 since 1990 are given in Fig. 5.10. Table 5-4 lists the top 3 countries in in-degree, out-degree, and PageRank centrality between 1990 and 2019. The results are obtained as follows.

Fig. 5.7. Top 3 countries in *ID* centrality and knowledge transfer path

Fig. 5.8. Top 3 countries in OD centrality and knowledge transfer path

Fig. 5.9. Top 3 countries in *PR* and knowledge transfer path

Table 5-4 Top 3 countries in *ID*, *OD*, and *PR* centralities since 1990

Centrality	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
In-degree	ARG	GNB	ARG	ARG	ARG	PAK	IDN	CHN	BRA	CHN	CHN	CHN	CHN	CHN	CHN
	YEM	MDG	THA	PHL	CHN	ARG	CHN	BRA	CHN	BRA	ARG	LKA	BRA	BRA	MEX
	CIV	CAF	CHN	MYS	COL	PHL	THA	COL	MEX	PER	BRA	BRA	MEX	LKA	IND
Out-degree	ES	FR	FR	US	US	US	US	US	US	US	US	US	FR	JP	US
	GB	GB	ES	FR	FR	FR	GB	FR	FR	FR	FR	FR	US	DE	FR
	FR	US	US	SG	JP	IFC	SG	GB	GB	JP	ES	GB	DE	FR	DE
PageRank	YEM	CHN	ARG	ARG	ARG	PHL	IDN	BRA	BRA	CHN	TZA	LKA	TLS	LKA	GEO
	CIV	PHL	THA	MYS	PHL	ARG	LAO	COL	CHN	THA	PHL	IND	ECU	CHN	CHN
	ARG	ARG	CHN	PHL	CHN	KHM	CHN	MMR	SLV	BRA	THA	BRA	CHN	ECU	MOZ
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
In-degree	CHN	CHN	CHN	CHN	BRA	BRA	IND	ZAF	BRA	BRA	BRA	BRA	EGY	MEX	MEX
	LKA	IND	IND	BRA	JOR	RUS	TUR	THA	MEX	MEX	PER	MEX	IDN	ZAF	UKR
	DZA	BRA	MEX	LKA	IND	IND	MEX	BRA	PER	PER	PHL	IDN	MEX	VNM	BRA
Out-degree	FR	SG	US	ES	ES	CHN	ES	DE	ES	ES	ES	IT	CHN	IT	CHN
	SG	FR	SG	US	FR	ES	CHN	CHN	DE	US	US	CHN	ES	FR	ES
	ES	ES	FR	SG	US	DE	US	US	CHN	FR	GB	ES	IT	ES	FR
PageRank	LKA	IND	IND	UGA	JOR	RUS	BWA	PER	PER	PER	PER	BRA	EGY	VNM	ARG
	CHN	MEX	PAK	LKA	TUR	COL	IND	LAO	BRA	SRB	COL	ECU	PER	COL	BRA
	ECU	LAO	PER	IRQ	BRA	IND	TUR	ZAF	GTM	BRA	PHL	COL	IRN	IND	CUB

Fig. 5.10. *ID* and *OD* centralities for different countries since 1990

(1) Despite the foreign-based partners of the same country are relatively fixed, the weight of their relationships may vary a lot with time. Fig. 5.7 shows that Argentina prefers to engage companies from Spain, the US, and France. China is more likely to bring in parties from Singapore and the US. The network size of each network is similar (min: 17, max: 25, mean: 23), indicating that countries are used to retrieving information from fixed countries. Table 5-4 shows that the most active actor is changing but some are always holding a lead role, including Brazil, Mexico, and India. In-degree centrality has shown three types of trends: a) it increases at the beginning and decreases later, such as in China. The possible reason is that enough knowledge has been gained by conducting a lot of PPP projects. For example, China has replaced most foreign investors with state-owned enterprises (Cheng et al. 2020), b) it keeps increasing, such as in Brazil and Mexico. This may be due to their weak ability in absorbing PPP knowledge because they still need to rely on others to develop PPP projects after many local projects are developed. The low absorbing ability has been treated as one of the main barriers in knowledge transfer (Liu and Wang 2018), and c) in-degree stays relatively steady, such as in Argentina.

(2) Knowledgeable countries are spreading PPP knowledge into more developing countries. The importance of a country in transferring knowledge is evolving, and its role can change from knowledge receiver to knowledge source. As shown in Fig. 5.8, unlike in-degree networks, the number of knowledge receivers corresponding to the top 3 knowledge sources is increasing, which grew from 26 to 52. That is to say, more and more developing countries intend to involve foreign parties. Out-degree of some

countries have undergone a rising trend, such as China. In other words, rather than continuing to involve others, these countries have become a knowledge broker who is in charge of bridging different groups in the network. Table 5-4 shows that the US has been the most active knowledge source before 2005. Out-degree centrality has shown two types of trends: a) out-degree maintains a relatively high level, such as the US, France, and Japan, and b) out-degree keeps going up, such as China. The impact of China has grown a lot since 1990, especially after 2008. Fig. 5.10 reveals that only 21 developing countries have the experience to participate in foreign-based PPP projects. Besides, most countries have much higher in-degree centrality than out-degree centrality that is below 10. In other words, these countries have to involve other countries in a PPP project due to a low knowledge level. However, some countries, such as China and Malaysia, act as knowledge brokers.

(3) Some developing countries have more popular PPP markets than others, and they may be vital in conveying PPP knowledge from their knowledge sources to other countries. Unlike out-degree centrality that reflects the importance of knowledgeable countries in transferring knowledge, PageRank can dig the hidden less-knowledgeable countries that can also be influential in knowledge transfer. Fig. 5.9 shows that the PageRank in each network has exhibited less variance. Two reasons can lead to a large PageRank for a country: a) it has a large in-degree centrality, such as Brazil and India in the network for 2000-2004, and b) it links to a country with high PageRank, such as Peru who has less in-degree centrality but is linked with India in the network for 2000-2004. These countries are central to transfer knowledge because they have received knowledge from a large number of other countries. Although they may not proactively pass PPP knowledge to other countries by joining foreign projects due to small out-degree centrality, they can be good knowledge sources where the engaged countries can obtain the knowledge left by former involved countries. Table 5-4 shows that Brazil and India always have a large PageRank since 1990. The reason may be Brazil's infrastructure is deficient although with bound natural resources, and India's economic structure is robust, which has attracted more international interests (Deloitte 2012). PageRank centrality has shown two types of trends: a) it keeps at a high level, such as in Brazil and India, and b) it increases in the beginning and decreases later, such as in China and Argentina.

In summary, the evolution of both explicit and implicit roles of various countries and their relationships has been exposed. This will guide decision-makers to choose the right partners according to the conditions of their countries.

5.5 Top 5 Countries in Different Sectors

To further analyze the importance of a country in different sectors, the top-ranked countries in transport, ICT, energy, W&S, and MSW sector are picked based on the network containing all projects from 1990 to 2019 as shown in Table 5-5. Besides, the correlation analysis is carried out between countries' out-degree centralities in different sectors.

Table 5-5 Top 5 countries in *ID*, *OD*, and *PR* centralities in five infrastructure sectors

Central ity	Transport		ICT		Energy		W&S		MSW	
	Countr y	Val ue	Countr y	Val ue	Count ry	Val ue	Countr y	Val ue	Count ry	Val ue
In- degree	India	57	Indones ia	6	Brazil	231	China	172	Mexico	5
	Brazil	46	Russia	5	Mexico	106	Mexico	42	Turkey	4
	Colom bia	39	India	5	India	94	Argenti na	16	Brazil	3
	Peru	35	Thailan d	4	Thailan d	79	Brazil	13	Colom bia	2
	Mexico	35	Brazil	4	Turkey	74	Algeria	13	Serbia	2
Out- degree	Spain	84	France	10	US	247	France	112	France	8
	US	57	US	10	Spain	171	Singap ore	55	Spain	4
	France	47	UK	6	China	170	Spain	41	China	3
	China	33	China	5	Japan	142	US	38	Japan	2
	Singap ore	28	Italy	3	Germa ny	140	UK	29	Austria	1
PageRa nk	Peru	1.17	Nepal	0.63	Peru	2.39	China	1.04	Brazil	0.53
	Colom bia	0.65	Cambo dia	0.55	Serbia	2.18	Colom bia	0.89	Colom bia	0.38
	Ecuado r	0.60	India	0.55	China	0.74	Mexico	0.82	Russia	0.32
	Brazil	0.59	Indones ia	0.47	Indone sia	0.66	Peru	0.69	China	0.30
	Russia	0.56	Uganda	0.33	Ugand a	0.60	Thailan d	0.66	Turkey	0.30

Table 5-6 The correlation coefficients of the *OD* centrality in different sectors

Sector	Transport	ICT	Energy	W&S	MSW
Transportation	1.000	-	-	-	-
ICT	0.951	1.000	-	-	-
Energy	0.846	0.821	1.000	-	-
W&S	0.734	0.773	0.390	1.000	-
MSW	0.581	0.678	0.414	0.774	1.000

In Table 5-5, the largest in-degree centrality for each sector appears in India, Indonesia, Brazil, China, and Mexico, respectively. Besides, French companies have transferred the most knowledge to other countries in three sectors, such as the SUEZ for the W&S sector and Alcatel-Lucent for the ICT sector. Spain companies are the most important in the transportation sector, and famous companies include Obrascón Huarte Lain and Gestamp. The US ranks first in the energy sector, in which Alliant Energy and Hunt Oil Company are based. Finally, China has the largest PageRank in the W&S sector, this can be explained by the largest in-degree centrality of 172, representing a large quantity of the inbound links. However, countries with maximum PageRank in other sectors are not the ones with the highest in-degree centrality. The reason for the high PageRank of these countries is that they have cooperated with other important countries in the network (Guevara et al. 2020).

Out-degree centrality reflects whether a country is popular among others or not, and it tells whether the country is a central knowledge source. To find the relationship between countries' positions in different sectors, the correlation coefficients are obtained. Table 5-6 shows that there are strong correlations between some sectors. A high correlation coefficient between two sectors suggests that a country based in the center of the knowledge transfer network in one sector is also in an important position in the other sector. The largest correlation coefficient, which is 0.951, is obtained between the transportation and ICT sectors. In other words, important knowledge sources in the transportation sector are more likely to be important in the ICT sector, such as the US, France, and China. The same phenomena can also be found between the transportation and energy sector (0.846), as well as the ICT and energy sector (0.821). Moreover, the smallest correlation coefficient, which is 0.390, is found between the energy and W&S sectors. In other words, important knowledge sources in the energy sector are not necessarily the important ones in the W&S sector. For

example, the US and Japan are ranked high in the energy sector but they have low out-degree centralities in the W&S sector.

5.6 Knowledge Flow Path Around the World

Countries in different regions may have different preferences in choosing partners. Furthermore, according to previous literature, an organization intends to collaborate with the partners with whom they have previously worked (Guevara et al. 2020). In pursuit of providing countries with a precise guide on how to choose appropriate partners, it is essential to have a clearer view of how PPP knowledge flows from mature markets to emerging ones on earth in the past decades. Fig. 5.11 gives the knowledge transfer path since 1990 around the world, where the diameter of the red circle represents the out-degree centrality, and the green line is the knowledge transfer path. The deeper the color of the line is, the higher the knowledge transfer extent is.

Fig. 5.11. Knowledge transfer path from 1990 to 2019

Some results could be obtained:

- 1) PPP knowledge is unevenly distributed on earth. The top 10 countries in out-degree centrality are the US, Spain, France, China, Germany, Japan, the UK, Singapore, Italy, and Canada, which have spread the most PPP knowledge to other regions. These countries are mainly from North America, the European Union, and EAP regions, which have participated in over 70% of the non-domestic PPP projects. However, less information has come from countries in the rest of the world, especially in the MENA and SAR regions. That is to say,

although many PPP projects have been developed around the world, most countries still lack enough PPP knowledge in the environment of PPP globalization. It is therefore recommended that the countries in regions with less PPP experience should engage experienced countries as advisers or sponsors.

- 2) Countries with qualified experts have different preferred regions when carrying out overseas projects. The most popular areas for the top 10 knowledge sources to spread PPP knowledge are LAC, LAC, EAP, SAR, ECA, EAP, EAP, EAP, LAC, and LAC regions, respectively. For example, 79.3% of foreign PPP projects by Spain are in the LAC region, 53.8% of foreign PPP projects by Japan, and 72.0% by Singapore are in the EAP region. Most countries are more likely to be involved in projects near the border. Therefore, two aspects should be taken into account when selecting foreign partners. On one hand, it is wise to invite influential partners in nearby countries as they have more experience in cooperating with the countries in neighbouring regions. On the other hand, foreign countries' policies should also be reviewed. For example, China has participated in many more PPP projects in the SAR region than other countries due to the policy of the "Belt and Road Initiative".
- 3) Different regions have different attractions for foreign participants. The percentage of projects with foreign participation in total PPP projects for AFR, EAP, ECA, LAC, MENA, and SAR region is 55.1%, 22.7%, 44.0%, 37.6%, 60.4%, and 20.4%, respectively. It can be found that the SAR region has the lowest percentage of projects with foreign participation, but the MENA region has the largest one. This phenomenon may mainly be caused by variation in the economic environment, ongoing support from the government, and legal framework. In all projects with foreign participation, the energy sector, especially the electricity part, has attracted the most foreign countries. Besides, the average foreign entrants in each foreign involvement project are 1.21, 1.22, 1.21, 1.20, 1.44, and 1.23, respectively. That is to say, more foreign countries have been involved in a single PPP project in the MENA region at the same time.

5.7 Summary

The adoption of the PPP procurement method can make an unneglectable commitment to the development of society, especially in developing countries.

However, many challenges exist in the process of implementing PPP projects. To improve the performance of PPP projects, it is, therefore, a prerequisite to have an understanding of the interactions among different countries in the PPP domain, which will contribute to the correct partner selection in the context of PPP globalization. This chapter aims to find the characteristics of the global PPP knowledge transfer networks from 1990 to 2019 in different dimensions. The SNA method has been adopted to analyze the PPI database. The outcomes of this chapter are:

1. The macro-level metrics suggest that an increasing number of developing countries have joined the PPP global market and they are more likely to involve more foreign countries in one PPP project at the same time.
2. The difference between the weighted density and unweighted density indicates that a large number of repeated relationships have been built between some countries. This has caused the uneven distribution of the importance and positions of countries in transferring knowledge.
3. The top-ranked countries in knowledge transfer are changing with time. However, countries like the US, the UK, and Germany are always active in the PPP knowledge transfer process.
4. The PageRank centrality shows that apart from the knowledgeable countries, some less-knowledgeable countries can also be in vital positions in spreading PPP knowledge, such as Brazil, Peru, and Serbia. Although they may be weak in transferring knowledge to other countries by joining foreign-based projects due to low out-degree centrality, these countries have involved more knowledgeable countries in previous projects, which can be an important knowledge source for the later collaborators.
5. Although countries have various positions in transferring knowledge in different PPP sectors, there is a significant positive correlation between countries' out-degree centralities in some sectors. The correlation coefficient varies between 0.390 and 0.951. In other words, some important countries in one sector are more likely to be vital in the other one. For example, France and China are important knowledge sources in both the transportation and ICT sectors.

Chapter 6 Failure Factors for PPP Contracts

6.1 Introduction

PPP models are becoming popular among various governments worldwide, particularly in developing countries, to contribute towards urban development. However, most developing countries do not have a mature framework that could predict the outcome of a PPP project in advance. As a result, contract failure is more likely to happen. It is argued that there is an increasing trend in contract failure due to the rising cost and reduction in available project financing caused by the global financial crisis (Harris and Pratap 2009).

The main objective of this chapter is to predict the final status of a PPP project using classification ML models and find out the primary failure triggers of the PPP contract. First, data sets are preprocessed to make them appropriate for analysis. Second, the performance of various ML models, including the random forest (RF) model, logistic regression (LR) model, k-nearest neighbors (KNN) model, LightGBM (LGB) model, XGBoost (XGB) model, and stack model are compared under various data sets and data balancing techniques. Finally, primary failure factors for the transportation sector, W&S sector, and energy sector are given.

6.2 Methodology

This section gives a comprehensive introduction to the proposed methodology. As shown in Fig. 6.1, the section is composed of four main modules: (i) data preparation, (ii) ML model, (iii) performance evaluation, and (iv) model interpretation.

Fig. 6.1. Framework for detecting PPP contract failure factors

6.2.1 Data Preparation

(1) Handling missing values

Approaching missing values is imperative to improve the accuracy of data mining, which relies on complete data sets (Al-Janabi and Alkaim 2020). In general, three common methods can be used to handle missing values. First, removing observations that contain missing values in any attribute. It is valid when the missing values appear only in a small part of observations. However, if an attribute has missing values in a large number of observations, it should be dropped. The disadvantage of this method is that the useful information in the data set may be ignored. Second, the data set can be manually checked by domain experts who will determine and enter the reasonable and feasible values based on knowledge or literature, which will be time-consuming in the case of large data sets. Third, carrying out missing value imputation automatically. Missing value imputation means replacing the missing values with an estimation based on non-missing values in other observations in the same attribute. The most often used techniques are filling the missing values with a global constant, the mean or the most frequent value of the current attribute, and clustering (Raja and Thangavel 2020). This research will handle the missing values by combining the clustering technique and domain knowledge.

The clustering-based method will group similar observations into the same cluster using the unsupervised algorithms, and the missing values can be filled based on the cluster information (Raja and Thangavel 2020). Rather than clustering the data set by algorithms, clustering is achieved based on prior knowledge and literature review in this research. For example, it can be assumed that the contract period of a PPP project may depend on the country that develops the project and the contract type. Therefore, the missing contract period of a BOT project in one country may be replaced with the average contract period of all BOT projects in that country.

(2) Handling categorical variables

Categorical variables are variables that have more than one possible value, classifying each observation into a particular group. Appropriate transformation should be done for the categorical variable before using the ML model for analysis. The most popular technique is converting the categorical variables into numerical values and labels (Liu

et al. 2019). The first method can be applied to ordinal variables with the natural order. For example, the income level of a country is an ordinal variable, which can be low, low-medium, upper-medium, and high. The second one is suitable for nominal variables. For instance, the primary source of revenue of a PPP project is a nominal variable with several various values, such as purchase agreement and user fees.

Values in an ordinal variable will be replaced with different numerical values according to their orders or ranks. For example, four levels in the income level variable can be assigned to 1, 2, 3, and 4, respectively.

The nominal variable can be replaced by a combination of binary variables that take a value of 0 or 1 depending on if a specific category is present in an observation or not. For example, the project type factor contains three unique values of greenfield, brownfield, and management & lease, based on which three new boolean variables “PF18-Greenfield”, “PF18-Brownfield”, and “PF18-Management & lease” can be generated. If one project is greenfield, the value for “PF18-Greenfield” will be 1, while the value for “PF18-Brownfield” and “PF18-Management & lease” will be 0.

(3) Data balancing

As previously mentioned, in binary classification problems, resampling can be achieved by oversampling and undersampling techniques. The most representative oversampling technique is SMOTE, which creates new observations by interpolating neighboring minority observations. The main advantage of SMOTE is that it can overcome the over-fitting problem to a large extent (Cheng et al. 2019). The undersampling technique is to reduce the number of majority samples, which may discard useful information in the majority classes (Zhu et al. 2020).

Data balancing will be conducted on the training data set alone to avoid data leakage (Schlögl et al. 2019; Zhang et al. 2017). In other words, the test data set is still imbalanced.

(4) Dimensionality reduction

Dimensionality reduction is useful when preprocessing the data set with a large number of attributes and observations. Dimensionality reduction, which reduces the high-dimensional data set to the low-dimensional one, can improve the performance of an ML model by eliminating insignificant attributes (Reddy et al. 2020). Principal

Component Analysis (PCA) is one of the most popular dimensionality reduction techniques and it can reduce the dimension of the data set by linearly transforming the interrelated attributes into a new set of uncorrelated ones named principal components (*PCs*) while retaining the most possible variation and information of the original data set (Abdi and Williams 2010). *PC* can be obtained by Eq. (6.1).

$$PC_i = a_{i1}x_1 + a_{i2}x_2 + \dots + a_{in}x_n \quad (6.1)$$

where i denotes the i th principal component, x_n is the n th attribute in the data set, and a_{in} is the loading of variable x_n for the principal component PC_i .

The importance of each *PC* depends on the variance of the original data set it retains. As the order of the principal component decreases, the retention of the variance by each principal component also decreases. Therefore, the first principal component has the maximum variance and is of the highest importance in determining the result of the dependent variable (Nobre and Neves 2019). As the results of PCA can be considerably affected by the scale of the features, the StandardScaler method, therefore, has been used to normalize the attributes before the PCA is fitted.

6.2.2 Machine Learning Models

(1) RF model

RF is an assembling method for classification and regression by aggregating the results of a series of decision trees (Zhao et al. 2020). A decision tree is composed of a set of inner nodes and leaf nodes, which represent the decision thresholds and prediction results, respectively (Liang et al. 2019). Fig. 6.2 gives an example of a decision tree with a depth of 3, where O_1 - O_3 are the attributes in the data set, C_1 - C_4 are the leaf nodes denoting predicted classes, and δ_1 - δ_3 are the thresholds.

Fig. 6.2. An example of the decision tree

RF model has inherited the advantages of the decision trees, and it can grow each tree by selecting random samples with replacement from the whole training data set. However, RF can provide a more precise and stable prediction. RF is robust in handling outliers of the data set, and it can capture the nonlinearities and relationships among high-dimensional variables (Maskey et al. 2020). The optimal hyper-parameters are needed to obtain a better prediction result of an ML model.

(2) LR model

LR model is used to predict the probability of an event (Tien Bui et al. 2019). This probability can be calculated by a sigmoid function, as shown in Eq. (6.2).

$$P(t) = \frac{e^t}{1 + e^t} \quad (6.2)$$

where t is the linear combination of independent variables of the data set, which can be calculated by Eq. (6.3).

$$t = b_0 + b_1x_1 + \dots + b_nx_n \quad (6.3)$$

Where x_n is the n th attribute in the data set, and b_n is the estimated coefficient from the data.

The main advantages of the LR model are that it has no requirement on the distribution of the variables in the data set and is easier and quicker to implement (Tien Bui et al. 2019).

(3) KNN model

KNN model is a case-based learning method, it only makes the decision based on a limited number of instances rather than the whole space. The main idea is that if most of the k nearest neighbors of an instance in the data set belong to a specified class, then this instance will be the same class as its neighbors (Gao and Li 2020). KNN models need the distance metrics, such as Manhattan distance, Minkowski distance, and Euclidean distance, to determine the neighbors. This research uses the Minkowski distance, which has been given by Eq. (6.4).

$$D_{Minkowski}(x, y) = \left(\sum_{i=1}^n |x_i - y_i|^p \right)^{\frac{1}{p}} \quad (6.4)$$

where x_i and y_i denote the coordinates of the vectors x and y , respectively. p is used to manipulate the method to calculate the distance between two points, and it can be any real value. When $p=1$ and $p=2$, Minkowski distance is the same with Manhattan distance and Euclidean distance, respectively. Therefore, the algorithm is more flexible by using the Minkowski distance. The default value of p is 2.

(4) LGB model

LGB model is one type of Gradient Boosting Decision Tree (GBDT) algorithms and it combines weak learners to generate a strong one (Ju et al. 2019). Unlike other GBDT algorithms that split the tree depth-wise or level-wise, the LGB model splits the tree leaf-wise with the best fit, as shown in Fig. 6.3. As a result, it can reduce more losses than other algorithms.

Fig. 6.3. Leaf-wise tree growth in LightGBM algorithm

(5) XGB model

XGB model is a boosting algorithm using decision trees (Jiang et al. 2019). The primary difference between the XGB model and other gradient boosting is that it adopts a special regularization technique to control the overfitting (Al Daoud 2019). As a result, it is much faster and more robust. XGB model is based on level-wise tree growth, which has been shown in Fig. 6.4.

Fig. 6.4. Level-wise tree growth in XGBoost algorithm

6.2.3 Model Stacking

Stacking means fitting the second classifier, meta-learner, based on the prediction results from a series of base learners in the first level (Pavlyshenko 2018). Fig. 6.5

gives a framework of the stacked model, where the C_n denotes the single classifier, such as the RF model as well as the LR model, and P_n denotes the prediction result of a single model. Besides, the meta-learner can be any other single classifier. In this research, a new LR model will be used for meta-learner. The stacking approach can reduce the inherent variance and bias of other models (Matlock et al. 2018). However, the disadvantage of the stacking model is that the training time is longer, and more computer memory is required.

Fig. 6.5. Stacking multiple classifiers into an ensemble model

6.2.4 Performance Evaluation

To evaluate the performance of ML models, evaluation metrics need to be determined. For a classification problem, the model performance can be assessed by the receiver operating characteristic (ROC) curve, the area under the ROC curve (AUC), recall, precision, precision-recall (PR) curve, accuracy, and F_β score. These metrics can be obtained based on the confusion matrix, which shows the result of a supervised ML model. Fig. 6.6 (a) gives a confusion matrix for binary classification, where the rows and columns denote the observations for predicted classes and actual classes, respectively. Besides, P (positive) and N (negative) are the numbers of real positive and real negative observations in the data set, respectively. TP (true positive) and TN (true negative) are the numbers of correctly detected observations in P and N, respectively. FP (false positive) is the number of negative observations incorrectly predicted as positive, and FN (false negative) is the number of positive observations incorrectly predicted as negative (Chou and Lin 2013).

		Actual class	
		P	N
Predicted class	P	TP	FP
	N	FN	TN

(a) Confusion matrix

(b) Class distribution

Fig. 6.6. Confusion matrix and distribution of predicted result

In binary classification tasks, to separate the positive class from the negative one, a decision threshold is defined. If the predicted probability of an observation is larger than the threshold, the label of the observation will be classified as the positive class, and vice versa. Fig. 6.6 (b) shows the distribution of the predicted results, where the dash vertical line is the decision threshold. For each threshold, a different confusion matrix will be generated. ROC curve is obtained by plotting the true positive rate (TPR) against the false positive rate (FPR) under different decision thresholds, which can be calculated by Eq. (6.5) and Eq. (6.6), respectively (Lin et al. 2017). The area under the ROC curve is AUC, which tells the capability of a model in distinguishing between different classes. AUC ranges from 0 to 1, and the higher the AUC, the better the model is. In the context of this research, a high AUC means good performance in differentiating the successful and fail PPP contracts. The accuracy, denoting the ratio of the correct predictions to the total predictions made, can be calculated by Eq. (6.7). However, both ROC and AUC are not sensitive enough to class distribution in an imbalanced data set, which may be misleading (Ye et al. 2019).

$$TPR = \frac{TP}{TP + FN} \quad (6.5)$$

$$FPR = \frac{FP}{FP + TN} \quad (6.6)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6.7)$$

To evaluate the classification performance of imbalanced data sets, recall, precision, PR curve, and F_β score may outperform AUC. PR curve is obtained by plotting precision against recall under different thresholds. The recall is the same as TPR. Precision is the ratio of the number of correctly predicted positive samples to that of the predicted positive samples, which can be calculated by Eq. (6.8) (Chou and Lin 2013). In practical situations, a trade-off should be made between precision and recall.

F_β score can combine recall and precision with different weights, which can be calculated by Eq. (6.9) (Lin et al. 2017). When the recall and precision are assigned the same weight, β will equal 1.0. Finally, F_β score turns into F_1 score, which will be used in this research.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (6.8)$$

$$F_\beta \text{score} = (1 + \beta^2) \frac{\text{precision} \cdot \text{recall}}{\beta^2 \cdot \text{precision} + \text{recall}} \quad (6.9)$$

6.2.5 Model Interpretation

The relationship between an independent variable and the dependent variable can be obtained by the correlation coefficient. The positive correlation coefficient means that the dependent variable tends to increase when one independent variable increases (Xu and Deng 2017). When predicting the PPP contract failure, if the failed projects are labeled as 1 and the successful ones are labeled as 0, the increase in the dependent variable denotes that the status of the project changes from 0 (successful) to 1 (fail). Therefore, if an independent variable is positively related to the contract failure, it will be categorized as the failure factor of PPP contracts.

To find the important independent variables that have a considerable contribution to the differentiation of various classes in the dependent variable, feature importance can be used as a criterion. Some studies have determined the feature importance by correlation coefficients, where the independent variables that have small correlation coefficients with the dependent variable will be neglected. However, the correlation coefficient only looks for linear correlations without capturing the combined effect of various factors on the target (Mangal and Holm 2018). A low correlation coefficient only means that there is no obvious linear relationship between the independent variable and the dependent variable, it does not indicate that the independent variable is not related to the dependent variable (Schober et al. 2018).

Therefore, the feature importance of an independent variable is measured based on its contribution to the prediction process, which can be obtained according to its loading in the first principal component of PCA (Holland 2008). In the context of contract failure prediction, the importance of each feature will be interpreted as the

ranking of the failure factor. The higher the variable importance of a failure factor, the more important it is.

6.3 Data Preprocessing

Three public databases have been analyzed to extract the factors that may impact the final status of a PPP project. As a result, twenty-one project-specific and twenty country-specific factors have been found for Data1. The whole data analysis process can be found in Fig. 6.7. Table 6-1 shows the distribution of the project status in the training and test data sets. Table 6-2 lists out the summary of the original attributes and their descriptive statistics, where “Missing value” denotes whether the attribute contains missing values or not, and “Data type” gives the value type of the attribute. In this research, the project-specific and country-specific factors are denoted by “PF” and “CF”, respectively. These factors are independent variables, and the final status of the project is the dependent variable.

Table 6-1 Distribution of project status in different PPP sectors

Sector	Training data set (original)			Training data set (after SMOTE)			Test data set		
	Total	Failed project	Ratio	Total	Failed project	Ratio	Total	Failed project	Ratio
Transportation	1169	91	7.78%	2156	1078	50%	293	23	7.85%
W&S	668	49	7.33%	1238	619	50%	168	12	7.14%
Energy	2076	66	3.18%	4020	2010	50%	519	16	3.08%

Fig. 6.7. The framework of predicting PPP contract failure

Table 6-2 Summary of variables for Data1

No	Attribute	Data type	Missing value	Source	Min	Mean	Max
PF1	Contract period (years)	Numeric	Yes	PPI	1.0	25.0	99.0
PF2	Cross-border project	Numeric	No	PPI	1	-	8
PF3	Percentage of private participation	Numeric	Yes	PPI	0	93.05	100.0
PF4	Physical asset	Numeric	Yes	PPI	0	195.9	14800.0
PF5	Project capacity	Numeric	Yes	PPI	Depends on different sectors.		
PF6	Project year	Numeric	No	PPI	1990	-	2019
PF7	Total investment	Numeric	Yes	PPI	0.03	228.1	35586.5
PF8	Bilateral support	Categorical	Yes	PPI	2 values: yes or no.		
PF9	Government granting contract	Categorical	Yes	PPI	3 values: federal, local, and state/provincial.		
PF10	Lending type	Categorical	Yes	PPI	4 values: IBD, IDX, IDB, and LNX.		
PF11	Multilateral support	Categorical	No	PPI	2 values: yes or no.		
PF12	Public disclosure	Categorical	No	PPI	2 values: yes or no.		
PF13	Renewable	Categorical	No	PPI	2 values: conventional and renewable projects.		
PF14	Subsector	Categorical	No	PPI	12 values: such as electricity.		
PF15	Segment	Categorical	No	PPI	33 values: such as highway.		
PF16	Source of revenue	Categorical	Yes	PPI	5 values: such as user fee.		
PF17	Sub-type of project	Categorical	No	PPI	10 values: such as BOT.		
PF18	Type of project	Categorical	No	PPI	3 values: such as greenfield.		
PF19	Unsolicited proposal	Categorical	No	PPI	2 values: yes or no.		
PF20	Sponsor number	Numeric	Yes	PPI	1	2	13

PF21	Foreign countries	Categorical	Yes	PPI	2 values: yes or no.		
CF1	CPI 2019	Numeric	No	PPI	1.00	1.22	1.92
CF2	Country IDA status	Categorical	No	PPI	3 values: IDA, Blended, and Non-IDA.		
CF3	Region by income level	Categorical	No	PPI	6 values: such as LAC.		
CF4	Administrative region	Categorical	Yes	PPI	6 values: such as MENA.		
CF5	Income level	Categorical	Yes	PPI	4 values: such as high income.		
CF6	Control of corruption	Numeric	Yes	WGI	-1.72	-0.38	1.03
CF7	Voice and accountability	Numeric	Yes	WGI	-2.20	-0.38	1.14
CF8	Rule of law	Numeric	Yes	WGI	-2.42	-0.32	1.08
CF9	Regulatory quality	Numeric	Yes	WGI	-2.45	-0.15	1.13
CF10	Political stability & absence of violence	Numeric	Yes	WGI	-2.86	-0.60	1.28
CF11	Government effectiveness	Numeric	Yes	WGI	-2.22	-0.09	1.27
CF12	Real effective exchange	Numeric	Yes	WDI	31.7	96.7	388.1
CF13	Tax as GDP	Numeric	Yes	WDI	0.89	12.29	110.18
CF14	Exports as % of GDP	Numeric	Yes	WDI	0.18	25.93	156.54
CF15	Imports as % of GDP	Numeric	Yes	WDI	0.10	27.65	191.46
CF16	Domestic credit to private sector (% of GDP)	Numeric	Yes	WDI	0.78	65.40	158.50
CF17	Electric power consumption (kWh per capita)	Numeric	Yes	WDI	13.5	1825.7	6687.7
CF18	Life expectancy (years)	Numeric	Yes	WDI	46.2	73.3	82.0
CF19	GDP deflator	Numeric	Yes	WDI	-26.3	30.0	26765.9
CF20	GDP per capita	Numeric	Yes	WDI	102.6	4510.3	15974.6

It can be found from Table 6-2 that twenty-one project-specific factors and five country-specific factors are extracted from the PPI database after removing the same features and features with more than 30% missing values. These factors can be divided into numerical and categorical types. Besides, PF1-PF19, CF1-CF5 are extracted from the PPI database directly, while factors PF20 and PF21 are calculated by feature engineering based on other factors. PF20 and PF21 are extracted from the variable “description” in the PPI database. PF20 is the number of sponsors of a project and PF21 suggests whether the foreign countries have been involved in a project or not. Besides, the number of factors obtained from the WGI and WDI databases is 6 and 9, respectively. Moreover, thirty factors in the PPI database and all factors in the WGI and WDI database have missing values, which should be imputed before analysis. As previously mentioned, the numerical attributes will be filled with the mean of existing values in the same cluster while the missing values in categorical features will be replaced by the mode in the same cluster. The specific methods are:

- Imputing numerical missing values. PF1 and PF5 are assumed to depend on the country, region by income level (CF3), and sub-type of the project (PF17). PF3, PF4, and PF7 are assumed to depend on the country, subsector (PF14), and sub-type of the project (PF17). PF20 is assumed to depend on the country and subsector (PF14). CF8, CF12-CF17 are assumed to depend on the region by income level (CF3).
- Imputing categorical missing values. PF8, PF9, PF10, PF16, and PF21 are assumed to depend on the country and subsector (PF14). CF4 and CF5 are assumed to depend on the region by income level (CF3).

In this research, the contract failure in three PPP sectors that contain failed projects, including the transportation sector, W&S sector, and energy sector, will be predicted. Fig. 6.7 shows that the traditional algorithms including the RF model, LR model, KNN model, LGB model, XGB model, stack model, and ANN model will be used. The data set will be split into the training data set and test data set with a ratio of 4:1, followed by the data preprocessing. Several steps need to be carried out sequentially:

- Missing value imputation. Fill the missing values using the mean or mode of the same feature from similar projects.

- Convert categorical variables into numerical ones. This is because the categorical variables could not be accepted by some algorithms directly (Awada et al. 2021).
- Data normalization. Some algorithms are sensitive to the scale of attributes, which should be converted to a similar range. StandardScale technique is adopted in this research.
- Data set balancing. It can be found from Table 6-1 that the ratio between the number of contract failure projects and total projects in the training data set for each sector is 7.78%, 7.33%, and 3.18%, respectively, indicating the large skewness in the class distribution. Therefore, for conventional algorithms, the imbalanced training data sets need to be converted into balanced ones. SMOTE and random undersampling techniques will be used to compare the influence of various resampling techniques.
- Dimensionality reduction. PCA is adopted to lower the dimensional space of the data sets and remove the correlated features. In this research, the number of *PCs* is 40 for the three sectors.

After the data sets are processed, the ten-fold stratified grid search is used on the training data set to select the optimal hyper-parameters of the models. Subsequently, these models with the optimized hyper-parameters are used as base models of a stack model. The stack model learns how to optimally combine the predictions from the base models in the meta-model layer using a logistic regression model. Finally, the well-trained traditional models and stack models are verified by the test data set.

6.4 Model Results and Performance

To obtain the optimized hyper-parameters for the model using the grid search technique, the domain of the hyper-parameters for each model should be given, as shown in Table 6-3. Some main parameters will be introduced.

Table 6-3 Hyper-parameters and their ranges for RandomizedSearchCV

Model	Parameter names	Count	Parameter values
RF model	n_estimators	10	200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000
	max_features	2	‘auto’, ‘sqrt’
	max_depth	10	10, 20, 30, 40, 50, 60, 70, 80, 90, 100
	criterion	2	‘gini’, ‘entropy’
	min_samples_split	3	2, 5, 10
	min_samples_leaf	3	1, 2, 4
	bootstrap	2	‘True’, ‘False’
LR model	penalty	2	‘l1’, ‘l2’
	C	10	0.001, 0.006, 0.036, 0.215, 1.29, 7.74, 46.4, 278.3, 1668.1, 10000
	solver	2	‘lbfgs’, ‘liblinear’
KNN model	n_neighbors	30	[1, 31)
LGB model	learning_rate	20	0, 0.005, 0.011, 0.016, 0.021, 0.026, 0.032, 0.037, 0.042, 0.047, 0.053, 0.058, 0.063, 0.068, 0.074, 0.079, 0.084, 0.089, 0.095, 0.1
	n_estimators	10	100, 200, 300, 400, 500, 600, 700, 800, 900, 1000
	num_leaves	6	4, 7, 10, 13, 16, 20
	colsample_bytree	4	0.5, 0.6, 0.8, 1.0
	subsample	3	0.6, 0.7, 0.8
	reg_alpha	3	0, 1, 1.2
	reg_lambda	3	0, 1, 1.2
XGB model	eta	20	0, 0.053, 0.105, 0.158, 0.211, 0.263, 0.316, 0.368, 0.421, 0.474, 0.526, 0.579, 0.632, 0.684, 0.737, 0.789, 0.842, 0.895, 0.947, 1.
	n_estimators	10	100, 200, 300, 400, 500, 600, 700, 800, 900, 1000
	max_depth	6	1, 4, 8, 12, 16, 20
	subsample	4	0.5, 0.6, 0.7, 0.8
	colsample_bytree	4	0.5, 0.6, 0.8, 1.0
	alpha	3	0, 1, 1.2
	lambda	3	0, 1, 1.2

1. “n_estimators” is the common parameter for the tree-based models, it is the number of decision trees to be constructed in the model. A large “n_estimators” does not mean a more precise result but indicates a longer time to run the model.

2. “max_depth” in the RF model and XGB model is the maximum number of levels in each decision tree. Increasing this parameter will make the model more complex and more likely to overfit, which means that the model will have a much better result on the training data set than that on the test data set.
3. “subsample” in the LGB model and XGB model is the fraction of observations to be selected for training each decision tree. Lower values can make the model more conservative and prevent overfitting.
4. “learning_rate” in the LGB model and “eta” in the XGB model denotes the step size shrinkage used in the update to prevent overfitting. The range is [0, 1]. A smaller value means fewer corrections for each tree will be added to the model, making the model more conservative.

6.4.1 Transportation Sector

Table 6-4 gives the hyper-parameters of the best models for various data sets under different resampling techniques. Fig. 6.8 gives the distribution of the AUC score of different models on different training data sets, where the boxplot from the left to right under the same model represents different data sets. Table 6-5 lists the AUC and the area under the PR curve (AUPRC) of the test data set, the best performance of which has been marked in bold and added an underscore. The corresponding performance of the model on the test data set can be found in Fig. 6.9 and Fig. 6.10. Besides, Fig. 6.11 gives the ROC curve, PR curve where the corresponding y value of the dashed line is the ratio between the number of actual positive samples and negative samples, and the confusion matrix of the best model. Table 6-6 gives the primary evaluation metrics of the selected model.

Table 6-4 Best parameters for models under SMOTE and undersampling techniques in the transportation sector

		Data1		Data2		Data3		Data4	
		SMOTE	undersampling	SMOTE	undersampling	SMOTE	undersampling	SMOTE	undersampling
RF model	bootstrap	False	False	False	False	False	False	False	False
	criterion	entropy	entropy	entropy	entropy	entropy	entropy	entropy	entropy
	max_depth	20	80	30	80	30	50	30	30
	max_features	sqrt	sqrt	sqrt	sqrt	sqrt	Sqrt	sqrt	Sqrt
	min_samples_split	2	5	10	10	2	10	5	5
	min_samples_leaf	4	2	2	4	1	2	2	2
	n_estimators	1600	1200	800	1400	400	1000	1600	2000
LR model	C	1668.1	1.292	0.215	1.292	0.215	7.743	1668.1	1.292
	solver	liblinear	liblinear	liblinear	liblinear	liblinear	liblinear	liblinear	liblinear
	penalty	l1	l1	l1	l1	l1	l1	l1	l1
KNN model	n_neighbors	25	11	29	11	28	4	18	4
LGB model	colsample_bytree	0.6	0.6	0.5	0.5	0.5	0.5	0.5	0.5
	learning_rate	0.047	0.026	0.011	0.016	0.053	0.089	0.089	0.089
	n_estimators	900	900	300	800	900	600	700	600
	num_leaves	16	20	20	20	16	10	20	20
	reg_alpha	0	1	1.2	1.2	1.2	1.2	1.2	1.2
	reg_lambda	1.2	1.2	0	1.2	0	1.2	1	0
	subsample	0.7	0.7	0.6	0.6	0.7	0.7	0.6	0.8
XGB model	alpha	1	1.2	1	1	1	1.2	1.2,	1.2
	colsample_bytree	1.0	0.5	0.8	0.5	1.0	0.6	1.0	0.8
	eta	0.158	0.053	0.368	0.105	0.526	0.053	0.737	0.316
	lambda	1.2	1.2	1	1	0	1	1.2	0
	max_depth	20	12	8	8	4	20	20	16
	n_estimators	400	300	300	100	600	400	400	200
	subsample	0.5	0.7	0.7	0.8	0.5	0.6	0.5	0.6

Fig. 6.8. AUC comparison on training data sets in the transportation sector

Table 6-5 AUC and AUPRC comparison on test data sets in the transportation sector

Resampling technique	Model	AUC				AUPRC			
		Data1	Data2	Data3	Data4	Data1	Data2	Data3	Data4
SMOTE	RF	0.794	0.793	0.786	0.783	<u>0.345</u>	0.341	0.277	0.311
	LR	0.730	0.777	0.760	0.772	0.189	<u>0.253</u>	0.252	0.241
	KNN	0.717	0.735	0.718	0.716	<u>0.325</u>	0.318	0.314	0.242
	LGB	0.727	0.773	0.721	0.802	0.244	<u>0.356</u>	0.229	0.299
	XGB	0.770	0.742	0.755	0.734	<u>0.290</u>	0.258	0.209	0.271
	Stack	0.766	0.785	0.762	0.775	0.341	<u>0.360</u>	0.289	0.315
Under-sampling	RF	0.767	0.774	0.766	0.756	0.328	0.320	<u>0.362</u>	0.298
	LR	0.698	0.724	0.706	0.728	0.208	0.254	0.219	<u>0.287</u>
	KNN	0.774	0.734	0.772	0.762	0.298	0.216	0.355	<u>0.361</u>
	LGB	0.746	0.752	0.741	0.735	0.279	0.240	<u>0.290</u>	0.273
	XGB	0.760	0.774	0.745	0.770	0.256	<u>0.301</u>	0.273	0.285
	Stack	0.784	0.783	0.798	0.784	0.381	0.358	<u>0.416</u>	0.380

Fig. 6.9. AUC and AUPRC for models under SMOTE technique in the transportation sector

Fig. 6.10. AUC and AUPRC for models under undersampling technique in the transportation sector

Fig. 6.8 shows that the SMOTE technique outperforms the undersampling technique in the transportation sector from the perspective of the training score. The AUC of the models varies between 62.3% and 81.9%. The maximum average AUC, which is 80.85%, of the four data sets is obtained by the RF model. However, the lowest variation has been found in the XGB+SMOTE+Data1 combination, which is 0.051.

The performance of the models has been improved by introducing new indicators in the transportation sector. Table 6-5 shows that the best AUC for the four data sets is 79.4%, 79.3%, 78.6%, and 80.2% under the SMOTE technique. That is to say, after introducing the newly proposed attributes, the value of the AUC score has improved by 0.8%. The best AUPRC for the four data sets is 34.5%, 36.0%, 31.4%, and 31.5%, where no improvement is found. However, a different tendency is displayed under the undersampling technique. In Table 6-5, the best AUC for the four data sets is 78.4%, 78.3%, 79.8%, and 78.4%, respectively, and the best AUPRC for the four data sets is 38.1%, 35.8%, 41.6%, and 38.0%, respectively. That is to say, the AUPRC has been increased by 3.5% by introducing countries' experience levels.

The best model on different data sets is different. Under the SMOTE technique, the RF model and stack model have a higher AUC score on the majority of data sets, followed by the LR model. However, the stack model performs better in the AUPRC under the undersampling technique, while the RF model ranks second. Table 6-5 reveals that the best combination for the transportation sector is the LGB+SMOTE+Data4 combination from the perspective of the AUC criterion (80.2%) when compared with other models that demonstrate a 69.8% to 79.8% AUC score.

At the same time, the Stack+UnderSampling+Data3 combination ranks highest from the perspective of the AUPRC criterion, which is at least 3.5% higher than others.

Fig. 6.11. ROC curve, PR curve, and confusion matrix for the selected model in the transportation sector

Table 6-6 Performance metrics of the selected model in the transportation sector

Sector	AUC	Recall	Precision	Accuracy
Transportation	0.80	65.2%	34.9%	87.7%

In Fig. 6.11, the model with the largest F_1 score based on the recall of 65.2% has been selected, in other words, fifteen failed projects will be picked with eight failed ones ignored. As a result, the best combination is the Stack+UnderSampling+Data3 combination, which achieved an accuracy of 87.7%, as shown in Table 6-6.

6.4.2 Water & Sewerage Sector

Table 6-7 gives the hyper-parameters of the best models for various data sets under different resampling techniques. Fig. 6.12 gives the distribution of the AUC score of different models on different training data sets, where the boxplot from the left to right under the same model represents different data sets. Table 6-8 lists the AUC and the AUPRC of the test data set, the best performance of which has been marked in bold and added an underscore, respectively. The corresponding performance of the model on the test data set can be found in Fig. 6.13 and Fig. 6.14. Besides, Fig. 6.15 gives the ROC curve, PR curve where the corresponding y value of the dashed line is the ratio between the number of actual positive samples and negative samples, and the confusion matrix of the best model. Table 6-9 gives the primary evaluation metrics of the selected model.

Table 6-7 Best parameters for models under SMOTE and undersampling techniques in the W&S sector

		Data1		Data2		Data3		Data4	
		SMOTE	undersampling	SMOTE	undersampling	SMOTE	undersampling	SMOTE	undersampling
RF model	bootstrap	False	False	False	False	False	False	False	False
	criterion	entropy	entropy	entropy	entropy	entropy	entropy	entropy	entropy
	max_depth	80	60	30	30	40	30	50	30
	max_features	sqrt	sqrt	sqrt	sqrt	sqrt	sqrt	sqrt	sqrt
	min_samples_split	5	5	10	5	10	5	5	5
	min_samples_leaf	4	2	2	4	1	4	2	4
	n_estimators	600	400	1800	2000	400	200	800	1200
LR model	C	0.006	0.215	1.292	0.036	0.036	0.215	0.036	0.006
	solver	liblinear	liblinear	liblinear	liblinear	liblinear	liblinear	liblinear	liblinear
	penalty	l1	l1	l1	l1	l1	l1	l1	l1
KNN model	n_neighbors	12	15	9	16	6	12	8	12
LGB model	colsample_bytree	0.8	0.8	0.5	0.8	0.6	0.8	0.8	0.5
	learning_rate	0.037	0.079	0.011	0.032	0.084	0.037	0.063	0.084
	n_estimators	1000	300	700	1000	900	200	900	400
	num_leaves	16	7	20	20	10	13	20	16
	reg_alpha	1	0	1	1.2	1.2	0	1	0
	reg_lambda	1.2	1.2	0	1.2	0	1.2	1.2	1
	subsample	0.6	0.8	0.6	0.8	0.8	0.6	0.7	0.8
XGB model	alpha	1.2	1	1.2	1.2	1	0	1.2,	1
	colsample_bytree	0.8	0.5	1	0.8	1.0	1.0	1.0	0.5
	eta	0.421	0.105	0.158	0.386	0.526	0.789	0.526	0.263
	lambda	0	1.2	0	1	1	1	1.2	0
	max_depth	8	20	16	4	8	4	16	12
	n_estimators	300	700	1000	400	200	700	400	100
	subsample	0.7	0.8	0.7	0.7	0.8	0.7	0.5	0.6

Fig. 6.12. AUC comparison on training data sets in the W&S sector

Table 6-8 AUC and AUPRC comparison on test data sets in the W&S sector

Resampling technique	Model	AUC				AUPRC			
		Data1	Data2	Data3	Data4	Data1	Data2	Data3	Data4
SMOTE	RF	0.798	0.779	0.834	0.794	0.297	0.318	<u>0.363</u>	0.350
	LR	0.708	0.768	0.777	0.789	0.324	<u>0.338</u>	0.330	0.309
	KNN	0.797	0.750	0.723	0.745	<u>0.451</u>	0.434	0.377	0.384
	LGB	0.755	0.744	0.808	0.803	0.335	0.422	<u>0.427</u>	0.389
	XGB	0.733	0.791	0.757	0.784	0.276	<u>0.419</u>	0.386	0.378
	Stack	0.764	0.792	0.784	0.798	<u>0.459</u>	0.429	0.448	0.455
Under-sampling	RF	0.873	0.829	0.821	0.841	0.340	<u>0.343</u>	0.256	0.241
	LR	0.823	0.767	0.733	0.711	<u>0.324</u>	0.308	0.243	0.296
	KNN	0.762	0.768	0.740	0.732	0.240	<u>0.245</u>	0.221	0.210
	LGB	0.798	0.736	0.730	0.761	<u>0.277</u>	0.136	0.199	0.172
	XGB	0.825	0.827	0.748	0.786	0.249	<u>0.274</u>	0.129	0.197
	Stack	0.844	0.807	0.801	0.814	<u>0.358</u>	0.331	0.267	0.249

Fig. 6.13. AUC and AUPRC for models under SMOTE technique in the W&S sector

Fig. 6.14. AUC and AUPRC for models under undersampling technique in the W&S sector

As in the transportation sector, Fig. 6.12 shows that the SMOTE technique outperforms the undersampling technique in the W&S sector from the perspective of training score. The minimum AUC score is 70.20% and the maximum one is 82.49%. On one hand, the maximum average AUC, which is 82.12%, of the four data sets is obtained by the RF model. On the other hand, the lowest variation has been found in the XGB+SMOTE+Data2 combination, which is 0.036.

Under the SMOTE technique, the best AUC for the four data sets is 79.8%, 79.2%, 83.4%, and 80.3%, respectively. That is to say, after introducing the PPP experience levels, the performance of AUC has increased by 3.6%. However, the countries' importance indexes have no contribution to the AUC score. The largest AUPRC for the four data sets is 45.9%, 43.4%, 44.8%, and 45.5%, respectively, where no improvement has been achieved by adding new factors. Under the undersampling technique, the best AUC for the four data sets is 87.3%, 82.9%, 82.1%, and 84.1%, respectively. The best AUPRC for the four data sets is 35.8%, 34.3%, 25.6%, and 29.6%, respectively. From this viewpoint, the newly proposed indicators can impede the performance of a model using the undersampling technique.

Under the SMOTE technique, the RF model and stack model have a higher AUC score on the majority of data sets than other models. However, the stack model performs better in the AUPRC under the SMOTE technique, followed by the KNN model, LGB model, and XGB model. By introducing the newly discovered indicators, the performance of the prediction has been improved. It can be seen from Table 6-8 that the best combination for the W&S sector is the RF+UnderSampling+Data1

combination from the perspective of the AUC score, while the Stack+SMOTE+Data1 model ranks highest from the perspective of the AUPRC criterion, which is 0.459.

Fig. 6.15. ROC curve, PR curve, and confusion matrix for the selected model in the W&S sector

Table 6-9 Performance metrics of the selected model in the W&S sector

Sector	AUC	Recall	Precision	Accuracy
W&S	0.83	66.7%	30.8%	86.9%

The model with the highest F_1 score under the recall of 66.7% has been selected, in other words, eight failed projects will be picked with four failed ones ignored, as shown in Fig. 6.15. As a result, the best combination is the XGB+UnderSampling+Data2 combination, which achieved an accuracy of 86.9%, as shown in Table 6-9.

6.4.3 Energy Sector

Table 6-10 gives the hyper-parameters of the best models for various data sets under different resampling techniques. Fig. 6.16 gives the distribution of the AUC score of different models on different training data sets, where the boxplot from the left to right under the same model represents different data sets. Table 6-11 lists the AUC and the AUPRC of the test data set, the best performance of which has been marked in bold and added an underscore, respectively. The corresponding performance of the model on the test data set can be found in Fig. 6.17 and Fig. 6.18. Besides, Fig. 6.19 gives the ROC curve, PR curve where the corresponding y value of the dashed line is the ratio between the number of actual positive samples and negative samples, and the confusion matrix of the best model. Table 6-12 gives the primary evaluation metrics of the selected model.

Table 6-10 Best parameters for models under SMOTE technique in the energy sector

		Data1		Data2		Data3		Data4	
		SMOTE	undersampling	SMOTE	undersampling	SMOTE	undersampling	SMOTE	undersampling
RF model	bootstrap	False	False	False	False	False	False	False	False
	criterion	entropy	entropy	entropy	entropy	entropy	entropy	entropy	entropy
	max_depth	10	10	70	80	10	40	60	60
	max_features	sqrt	sqrt	sqrt	sqrt	sqrt	sqrt	sqrt	sqrt
	min_samples_split	5	5	5	10	5	5	5	5
	min_samples_leaf	2	2	2	4	4	4	2	4
	n_estimators	1000	400	1200	1000	200	400	1600	400
LR model	C	0.036	1.292	0.036	0.215	0.001	0.036	7.743	0.036
	solver	liblinear	liblinear	liblinear	liblinear	liblinear	liblinear	liblinear	liblinear
	penalty	l1	l1	l1	l1	l1	l1	l1	l1
KNN model	n_neighbors	20	9	17	11	28	9	25	9
LGB model	colsample_bytree	0.6	0.5	0.5	0.5	0.5	0.6	0.8	0.6
	learning_rate	0.026	0.089	0.005	0.016	0.005	0.026	0.005	0.005
	n_estimators	200	300	700	800	400	400	400	400
	num_leaves	7	7	16	20	20	10	16	10
	reg_alpha	1	0	0	1	0	1	1.2	0
	reg_lambda	1.2	1	1	0	1.2	1	0	0
	subsample	0.8	0.8	0.6	0.6	0.7	0.6	0.6	0.6
XGB model	alpha	0	1	1.2	1	1.2	0	1	1.2
	colsample_bytree	1	0.6	0.8	0.5	1.0	1.0	0.8	1
	eta	0.053	0.316	0.158	0.053	0.579	0.263	0.421	0.842
	lambda	1	0	1	1	0	1	1.2	1.2
	max_depth	16	4	8	20	20	16	4	1
	n_estimators	900	900	500	900	400	500	800	400
	subsample	0.7	0.7	0.5	0.8	0.7	0.8	0.7	0.8

Fig. 6.16. AUC comparison on training data sets in the energy sector

Table 6-11 AUC and AUPRC comparison on test data sets in the energy sector

Resampling technique	Model	AUC				AUPRC			
		Data1	Data2	Data3	Data4	Data1	Data2	Data3	Data4
SMOTE	RF	0.870	0.867	0.865	0.872	0.168	<u>0.229</u>	0.168	0.227
	LR	0.825	0.816	0.775	0.807	0.158	<u>0.139</u>	0.110	0.121
	KNN	0.805	0.784	<i>0.807</i>	0.812	0.214	<u>0.231</u>	0.132	0.164
	LGB	0.866	0.756	0.873	0.856	0.158	0.111	0.155	<u>0.223</u>
	XGB	0.872	0.881	0.885	0.830	<u>0.279</u>	0.273	0.201	0.204
	Stack	0.856	0.853	0.853	0.847	0.164	0.219	<u>0.236</u>	0.206
Under-sampling	RF	0.808	0.749	0.799	0.806	0.103	0.065	<u>0.114</u>	0.100
	LR	0.810	0.790	0.765	0.761	0.127	<u>0.161</u>	0.139	0.140
	KNN	0.665	0.694	0.660	0.699	0.060	0.059	0.064	<u>0.065</u>
	LGB	0.758	0.686	0.750	0.765	<u>0.075</u>	0.051	0.063	0.074
	XGB	0.784	0.710	0.721	0.751	<u>0.115</u>	0.068	0.077	0.083
	Stack	0.808	0.755	0.766	0.790	0.113	0.080	<u>0.143</u>	0.105

Fig. 6.17. AUC and AUPRC for models under SMOTE technique in the energy sector

Fig. 6.18. AUC and AUPRC for models under undersampling technique in the energy sector

Like the transportation sector and the W&S sector, Fig. 6.16 shows that the SMOTE technique outperforms the undersampling technique in the energy sector from the perspective of the training score. The AUC of the models varies between 70.80% and 81.21%. The maximum average AUC, which is 80.51%, of the four data sets is obtained by the RF model. Besides, the lowest variation has been found in the KNN+undersampling+Data4 combination, which is 0.043. In other words, the new factors have made the model more robust.

Under the SMOTE technique, the best AUC for the four data sets is 87.2%, 88.1%, 88.5%, and 87.2%, respectively. That is to say, after introducing the PPP experience levels, the performance of AUC has improved by 1.3%. The best AUPRC for the four data sets is 27.9%, 27.3%, 23.6%, and 22.7%, respectively. Under the undersampling technique, the best AUC for the four data sets is 81.0%, 79.0%, 79.9%, and 80.6%, respectively. The best AUPRC for the four data sets is 12.7%, 16.1%, 14.3%, and 14.0%, respectively.

Under the SMOTE technique, the RF model and XGB model have a higher AUC on the majority of data sets, followed by the stack model. However, the stack model and XGB model perform better in the AUPRC, followed by the RF model and KNN model. By introducing the newly discovered indicators, the performance of the prediction has been improved. It can be seen from Fig. 6.17 and Fig. 6.18 that the best combination for the energy sector is the XGB+SMOTE+Data3 combination from the perspective of the AUC criterion, while the XGB+SMOTE+Data1 model ranks highest from the perspective of the AUPRC criterion.

Fig. 6.19. ROC curve, PR curve, and confusion matrix for the selected model in the energy sector

Table 6-12 Performance metrics of the selected model in the energy sector

Sector	AUC	Recall	Precision	Accuracy
Transportation	0.81	62.5%	22.2%	92.1%

The model with the highest F_1 score under the recall of 62.5% has been selected, in other words, ten failed projects will be picked with six failed ones ignored, as shown in Fig. 6.19. As a result, the best combination is the KNN+SMOTE+Data3 combination, which has achieved an accuracy of 92.1%, as shown in Table 6-12.

Overall, the AUC of the selected model for the three sectors is 0.80, 0.83, and 0.81, respectively. According to (Yang and Berdine 2017), the AUC larger than 0.8 can be thought to have outstanding discrimination. This indicates that the model can separate the failed and successful projects well. An increase in the recall can lead to a drop in precision, which depends on the position of the decision threshold. A low recall means most contract failure projects cannot be correctly forecasted, and a low precision means some successful projects will be identified as failed ones. Therefore, an appropriate threshold selection should be conducted based on the practical problem. As the main aim of this chapter is to ease the process of feasibility study of a PPP project, the projects with a high probability of failure should be detected as many as possible to avoid investment failure. In other words, a high recall is expected in this context, therefore, the cut-off point for the three sectors is located at 13.4%, 66%, and 85%, respectively. That is to say, any project that has a failure probability larger than these thresholds will be predicted as a failed project. From the point of project

selection, these projects are not recommended for private sectors with low risk-bearing ability and limited resources (Armaneri et al. 2010).

6.5 Failure Factors

To have a clear view of how different factors influence the final status of a PPP project. The correlation coefficients are calculated between each independent variable and the dependent variable. Table 6-13 demonstrates the top 15 failure factors that have the largest feature importance and the correlation coefficients in Data1.

Table 6-13 Failure factors and their importance in different sectors

No	Transportation sector		W&S sector		Energy sector	
	Failure factor	Correlation	Failure factor	Correlation	Failure factor	Correlation
1	CF19	0.058	CF15	0.232	CF19	0.043
2	CF12	0.047	CF14	0.192	CF1	0.596
3	PF3	0.075	CF1	0.606	PF20	0.243
4	PF20	0.067	PF7	0.400	PF1	0.123
5	PF4	0.061	PF16-Other	0.374	CF5	0.084
6	PF5	0.008	CF12	0.065	PF5	0.353
7	PF1	0.063	PF1	0.025	PF7	0.270
8	CF15	0.186	PF5	0.429	PF9-Federal	0.041
9	CF1	0.339	PF4	0.189	PF16-Other	0.368
10	CF14	0.137	CF13	0.033	PF17-BROT	0.141
11	CF5	0.018	CF3-SSF	0.016	CF4-SSA	0.013
12	PF16-Other	0.127	CF4-SSA	0.016	CF3-SSF	0.010
13	CF13	0.065	PF11-Yes	0.131	PF19_No	0.095
14	PF9-Federal	0.179	PF9-State/Provincial	0.072	PF8_No	0.085
15	CF3-LAC	0.080	PF20	0.288	PF12_No	0.129

Note: SSA = Sub-Saharan Africa (excluding high income) according to the PPI database.

The *t*-test has been carried out to obtain the significance level of the coefficient. The sample sizes of the three sectors are 2156, 1238, and 4020, respectively, which are very large values. The *p* value obtained for each coefficient value in the Table 6-13 is

therefore pretty small (much smaller than 0.05), indicating high importance levels. It can be seen from Table 6-13 that there are some common important failure factors in three PPP sectors. They are explained as follows.

- CPI 2019 (CF1). CPI is used to measure the risk of inflation or deflation, and a high CPI means the low purchasing power of services and goods (Sun et al. 2019). Inflation has an incentive to erode the real value of the debt, and it can impact PPP projects by increasing the material price, worker's salary, and the cost of hiring equipment and consultation services. It may lead to a high risk of cost overrun during the construction phase (Musarat et al. 2020). Moreover, for the projects that relied on the payment from end-user fees, such as water projects, inflation may lower the operating margins of private sectors in the operation phase. As it is less likely for the government to increase the user fees and to fill the service price gap due to inflation, the private sectors may have to terminate the projects.
- Sponsor number (PF20). Sponsors in a PPP project can bring more various technologies and knowledge to the project, which can be important to the success of the project. However, with the rise in the number of sponsors, different priorities, responsibilities, and capabilities of stakeholders may become a source of disputes and interest conflicts (Shrestha et al. 2017). If these interests are not well balanced, enhanced cooperation among different sponsors would not be achieved, increasing the chance of contract failure. Besides, a larger number of sponsors also indicates more transaction costs will be spent on coordination.
- Total investment (PF7) and project capacity (PF5). An increase in the scale of the project may make the project more complicated and risky. The reason is that the rise in project size may increase the strain on the resources and experience of the project company (Schleifer et al. 2014).
- Contract period (PF1). A long contract period can make a PPP project riskier. This is in contrast to the claims of some previous research, where it is asserted that a longer PPP contract relates to a better PPP performance (Klijn and Koppenjan 2016). However, some studies also obtained a similar conclusion (Wang et al. 2018). A long-term contract can be inflexible when facing a variety of unforeseen

and unexpected events that may have a negative influence on the value for money, such as changes in demands of users, competition from new and cheaper products, and fluctuation of inflation rates. These events can cause severe results to both public and private sectors, particularly in less-experienced countries if variation provisions have not been properly set in the contract.

- Source of revenue (PF16). The projects, whose revenues cannot be guaranteed, have a higher probability to fail than others. Unlike a purchase agreement, which is a long-term contract for purchasing the product at the agreed quantity and price, other revenue sources, such as user fees, cannot guarantee a stable cash flow due to the change in the demands and competitions from other products and services, which can increase the risk of both parties (Mendicino et al. 2019). As a result, the contract has to be terminated before the actual expiry date.

However, different sectors have different failure factors. The W&S sector and energy sector are more sensitive to the income level of a country. For example, these projects based in the SSF region, which is low-income level, are more likely to undergo a contract failure. For the transportation and energy sectors, the projects granted by the federal are more likely to fail. However, the state or provincial projects in the W&S sector are easier to fail. In other words, the lower the administrative ranking, the larger the probability for a W&S project to fail, especially in poor regions. The similar conclusion has been obtained by Harris and Pratap (2009), as well as Araral (2009). The reason is that water has its unique characteristics and is different from other products, such as power. For example, water is essential for life, which should be controlled by governments to provide low-price or even free products to the poor. However, privatization or controlled by low-level administrations means that private sectors may raise the water fees to cover the cost and make a profit. As a result, there will be an intense interest dispute between the private sectors and consumers.

6.6 Summary

Engaging private sectors in providing public infrastructure can help to lower the financial burdens of the governments and provide better services. Although PPP models have been utilized around the world, PPP contract failure has appeared in many projects, especially in the projects held by developing countries that are faced

with unpredictable environments and a shortage of management experience (Shrestha et al. 2017). To empower PPP practitioners with the ability to conduct the viability analysis of a PPP project, this research has applied different ML models to provide an early prediction of the final status of a PPP project in different sectors. The conclusions of this research are:

1. Different combinations and balancing techniques have various performances for different PPP sectors. From the perspective of the area under the PR curve, the Stack+UnderSampling+Data3 combination, RF+SMOTE+Data1 combination, and XGB+SMOTE+Data1 combination rank highest in the transportation sector, the W&S sector, and the energy sector, respectively.
2. The recall of 80.0%, 83.0%, and 81.0% has been achieved by setting the decision threshold of 13.4%, 66%, and 85% for the transportation sector, the W&S sector, and the energy sector.
3. The relationship between each factor and contract failure has been explored, the results show that factors have different correlation relationships with PPP contract failure. Factors that are positively related to the contract failure are identified as failure factors of a PPP contract, such as CPI, total investment, and project capacity.
4. The importance of each failure factor has been obtained based on the result of variable importance in PCA. The top-ranked failure factors vary with the PPP sectors.
5. A high correlation coefficient between an independent variable and the dependent variable does not indicate the high importance of a failure factor. The variable can be important even though the correlation coefficient is low.

From the viewpoint of public authorities. Decision-makers can evaluate the initial feasibility of the project by predicting the final status of the project using the selected ML model. First, by referring to the detected failure factors, the public sectors can adjust the variables of the project to minimize the probability of contract failure. Second, the relative importance of the failure factors can help government have a clearer view of the risk related to the projects, which can give governments the stronger bargaining ability to avoid the overpromised guarantees and supports to the

private sectors. This can protect the interests of taxpayers and gain value for money. Finally, a PPP guideline considering the risk mitigation and monitoring can be compiled to improve the performance of the domestic PPP projects and encourage more private investors to participate in the PPP projects.

From the viewpoint of the private sector. On one hand, they could select promising projects based on the detected failure factors, such as projects granted by non-federal governments. This may lower the probability of early termination of the projects, especially in unfamiliar foreign countries. On the other hand, sound measures can be taken when signing the contract with authorities to mitigate the risks introduced by high-ranked failure factors. For example, the inflation risk can be neutralized by the indexation mechanism. Finally, the private sectors can determine whether to invest in projects with different failure probabilities according to their risk-bearing ability.

Chapter 7 ECS-ML Models For PPP Contract Failure Prediction

7.1 Introduction

The principle of ML classification algorithms is to minimize the misclassification errors, which have been assumed to be equal in most ML models. This is often not the case for imbalanced classification problems. As previously mentioned, failing to detect a positive or minority class is usually worse than missing an example from the negative or majority class. In all of these situations, a false negative misclassification is more costly than a false positive one (Brownlee 2020). In the context of PPP contract failure prediction, investing in a project that is predicted to be successful could cause a huge cost to the sponsors if the project fails. However, giving up a successful PPP project should have minor losses. ECS-ML is a type of learning that considers the misclassification costs of each sample in the data set (Ling and Sheng 2010). By ECS-ML models, the results of the ML model can be intuitively expressed in financial or business terms, such as cost-saving.

The main objective of this chapter is to implement the ECS-ML model in the process of PPP contract failure prediction. First, the concept of the cost matrix is given and the process of implementing an ECS-ML model is provided. Second, a traditional ANN model is used to predict PPP contract failure. Third, the ECS-ML model is achieved based on the LGB model, XGB model, and ANN model. The performance including the AUC score and cost-saving of both ECS and traditional ML models is compared. Finally, the sensitivity analysis is carried out, and the model selection measures are put forward to guide the model selection under different requirements for various users.

7.2 Methodology

Fig. 7.1 indicates that the proposed methodology is composed of five main modules: (i) ANN model, (ii) cost matrix, (iii) loss function development, (iv) loss function implementation, and (v) evaluation metrics. The data sets that are used to train and verify the model have been processed in the last chapter. Therefore, data preprocessing is not required in this chapter.

Fig. 7.1. Framework for PPP contract failure prediction using ECS-ML model

7.2.1 ANN Model

ANN model has been used for data analysis in various domains, such as the health field (Musleh et al. 2019), sediment load prediction (Moeeni and Bonakdari 2018), and structural monitoring (Gomes et al. 2019). For a classification problem, the data set could be denoted by $S = \{(x_j, y_j)\}$ where x_j and y_j denote the feature space and label of the sample j , respectively. The ANN model can be used to predict the value of y_j based on the input x_j . Fig. 7.2 gives the basic structure of the ANN model.

Fig. 7.2. The basic structure of the ANN model

Generally speaking, an ANN model is composed of the input layer, hidden layer, and output layer. The basic principle of an ANN model is that it will transmit the weighted values of each neuron in the last layer to the next layer. The training process is to

obtain the optimized weights, such as ω_{21} in Fig. 7.2. The number of the input layer and the output layer is 1. However, there can be a series of hidden layers. The number of neurons in the input layer corresponds to the number of features in each sample, and the number of neurons in the output layer equals the number of labels of the target variable. However, the number of hidden layers and their neurons are difficult to determine. Therefore, the main problem in building an ANN model is to pick the appropriate values for these parameters (Saritas and Yasar 2019).

Like other ML models, ANN is also trained using an optimization process. A loss function is also required to calculate the model error. In a binary classification problem, the common loss function for an ANN model is the cross-entropy function (Golik et al. 2013). Other hyper-parameters are epoch and batch size. The number of the epochs defines the times that the learning algorithm will work through the entire training data set, and batch size is the number of samples that have been used before updating the parameters of the model. More specifically, the domain of the epoch is between 1 and infinity, while the range of the batch size is between 1 and the number of samples in the training data set. In this research, the number of neurons in the input layer and output layer is the number of *PCs* and 1, respectively. Besides, two hidden layers, with the number of neurons of 50 and 30, are added for each model.

7.2.2 Cost Matrix

The cost matrix indicates the cost of misclassifying the outcome of a project (Bahnsen et al. 2014). Table 7-1 exhibits a typical cost matrix for the binary classification problem, where C_{TP} and C_{TN} represent the cost of correctly classifying a positive sample and a negative sample, C_{FP} and C_{FN} represent the cost of misclassifying a negative sample and a positive sample. Table 7-2 gives the summary of the return on equity (*ROE*) and dividend payout ratio (*DPR*) of some companies that have been involved in the PPP projects. Table 7-3 summarizes the final values of each parameter for different finance schemes.

Table 7-1 Cost matrix for the sample in a classification problem

	Actual Positive ($y=1$)	Actual Negative ($y=0$)
Predicted Positive (c_1)	C_{TP}	C_{FP}
Predicted Negative (c_0)	C_{FN}	C_{TN}

Table 7-2 The *ROE* and *DPR* of some companies

Sector	Company name	Headquarters	ROE (%)	DPR
Transportation sector	Bollore Group	France	2.41 - 13.85	0 - 0.75
	A.P. Moller - Maersk	Denmark	-5.93 - 18.15	0.15 - 1.18
	Fraport	Germany	-17.84 - 11.78	0 - 0.52
	Sacyr	Spain	5.16 - 10.8	-
	Acciona	Spain	-46.63 - 11.93	0.26 - 0.97
W&S sector	SUEZ	France	-4.7 - 7.20	0 - 1.44
	Veolia Environnement	France	-6.56-10.5	0.73-2.63
Energy sector	Alliant Energy	the US	9.79 - 11.68	0.57 - 0.71
	Berkshire Hathaway Energy Company	the US	1.15 - 25.10	-
	Siemens Gamesa	Spain	48.74 - 41.92	0 - 0.56
	MidAmerican Energy Company	the US	11.35 - 12.2	-
	J-Power	Japan	5.3 - 9.1	-
	Gazprom	Russia	0.94 - 19.06	0.07 - 2.69
	Aggreko	UK	-8.99 - 30.68	0 - 0.68

Note: the data is obtained from https://www.gurufocus.com/new_index/

Table 7-3 Values of the parameters for various finance schemes

<i>R</i>		<i>ROE</i>		<i>DPR</i>		<i>r</i>	
Project finance	Corporate finance	Project finance	Corporate finance	Project finance	Corporate finance	Project finance	Corporate finance
0.3	-	15%	12%	70%	60%	7%	7%

In traditional ML algorithms, the cost for the correct classification and misclassification is assumed to be $C_{TP} = C_{TN} = 0$ and $C_{FP} = C_{FN} = 1$, respectively. However, the latter assumption is not reasonable for an imbalanced classification problem. Therefore, the cost for misclassifying a negative sample (cost for false positive) and the cost for misclassifying a positive sample (cost for false negative) need to be redefined.

(1) Cost for false positive

The cost for misclassifying a negative sample means the cost of failing to detect a successful project. It is assumed that the capital that should have been invested in a

PPP project by sponsors will be used for other projects with corporate finance when the project is predicted to fail. However, the higher level of leverages and *ROE* of the project finance means a higher profit (Engel et al. 2010). The gap in their profits is treated as the cost for misclassifying a negative sample. In a PPP project, the net income in each year is used for debt repayments, dividends, and reinvestment (Sirtaine et al. 2005). The profit of sponsors is primarily composed of the dividends, rising share price due to the reinvestment, and the terminal value at the end of the operation. In this research, it is assumed that the annual net income will be immediately distributed to the shareholders in the form of dividends after deducting the amortization of the debt service, and the profit of the sponsors is only from the dividend. This assumption is rational because the SPV aims to generate as-early-as-possible cash flows to investors, and there is a low need for reinvestment (Comer 1996; Leviäkangas et al. 2014). As a result, the equity of the project will keep stable during the project.

Therefore, the potential profit that should have been derived by sponsors from investing in a PPP project will be measured by the present value of all dividends during the contract period T . For project j , the dividend in one specific year can be calculated by Eq. (7.1) (Bodmer 2014).

$$d_{ji} = NI_{ji} \times DPR_{ji} \quad (7.1)$$

where NI_{ji} and DPR_{ji} are the net income and the DPR of project j in the i th year, respectively.

The NI_{ji} for the project j in the i th year can be obtained by Eq. (7.2) (Bodmer 2014).

$$NI_{ji} = ROE_{ji} \times E_j \quad (7.2)$$

where ROE_{ji} is the ROE of the i th year, and E_j is the equity committed by sponsors after the debt being drawn.

The ratio R_j between the equity and total investment of project j can be calculated by Eq. (7.3).

$$R_j = \frac{E_j}{E_j + D_j} = \frac{E_j}{I_j} \quad (7.3)$$

where the D_j and I_j are the debt and total investment of the project j , respectively.

Therefore, the dividend in the i th year for the shareholder can be obtained by combining Eq. (7.1), Eq. (7.2), and Eq. (7.3).

$$d_{ji} = ROE_{ji} \times R_j \times I_j \times DPR_{ji} \quad (7.4)$$

During the contract period, the total dividends considering the time value of money for project j can be calculated by Eq. (7.5).

$$d_j = \sum_{i=1}^{i=T} \frac{d_{ji}}{(1+r)^i} = \sum_{i=1}^{i=T} \frac{ROE_{ji} \times R_j \times I_j \times DPR_{ji}}{(1+r)^i} \quad (7.5)$$

where r is the discount rate.

Finally, the cost of missing a successful PPP project would be:

$$C_{FP_j} = d_{pj} - d_{cj} \quad (7.6)$$

where d_{pj} and d_{cj} are all dividends for project j with project finance and corporate finance, respectively.

Different sectors have different risk levels (Gatti 2018). For example, the energy sector is generally less risky than the transportation sector. This could be reflected by the debt service coverage ratio (DSCR). The common DSCR for the transportation sector is 1.25-1.5, while this value for the water and the energy sectors is about 1.35-1.40 and 1.2-1.3, respectively. Therefore, the ROE and DPR should vary with each sector. In this research, the value for these indicators is assumed to be the same in different sectors as it is difficult to distinguish the difference using the currently available information. Moreover, it is difficult to obtain transparent data to calculate the financial indicators of a project. Some assumptions are made:

- The ratio R is assumed to be 0.3. In a project finance initiative, the equity investors have the motivation to involve the debt as much as possible to improve the ROE . However, due to the financial crisis in these years, higher-level equity is required to bear risks. For example, the proportion of the equity in total investment rises from 0.2 to 0.3 for PPP energy projects (Cuttaree et al. 2009; De Marco and Mangano 2017). Besides, according to the toolkit by the Public-Private Partnership Legal Resource Center (PPPLRC) of the World Bank, the debt-to-equity ratio for a highway project is about 70:30 to 75:25 (World Bank 2009). In this research, this ratio is assumed to be 0.3 for all sectors.

- The *ROE* is the same during the contract period. Inter-American Development Bank (IDB) surveyed 50 experts that have participated in the Brazil PPP projects. 88% of the respondents thought that the *ROE* is between 10% and 18% (Queiroz et al. 2014). Moreover, the expected *ROE* for PPP projects in China is above 15% (Linh et al. 2018). In this research, the *ROE* is assumed to be 15% during the operation period of a PPP project. The *ROE* for the corporate finance is obtained by referring to the companies that have been involved in the PPP projects. Table 7-2 shows that the average *ROE* for most companies is about 9% to 13%. Therefore, the *ROE* for conventional projects is assumed to be 12%.
- The *DPR* is the same during the contract period. Few relevant studies have been found for this indicator. It is found that the *DPR* in twelve Portuguese PPP projects varied between 57% and 93% from 2003 to 2011 (Domingos 2013). Therefore, the *DPR* for all PPP projects is assumed to be 70%. Table 7-2 shows that *DPR* for different companies varies a lot. As previously mentioned, the *DPR* of a corporate company is usually lower than that of a project company, and it is assumed to be 60%.
- Discount rate r . The discount rate reflects the time value of money, and different countries have different criteria and reasons to select a discount rate for PPP projects (Copiello et al. 2017; Luo et al. 2021). Australian jurisdictions use a discount rate of 7% for most infrastructure projects (Terrill and Batrouney 2018). Zwalf et al found that the discount rate changes from 3.94% to 10.15% in 9 PPP projects in various countries (Zwalf et al. 2017). Pellegrino et al assumed the fixed discount rate of 5% for an Italian PPP project (Pellegrino et al. 2019). Hu et al have used the discount rate of 4% for a highway project in China (Hu and Han 2018). Another research found that 45% of the countries use the same single discount rate for all PPP projects, and 35% of countries use the same discount rate for traditional infrastructure projects (Burger and Hawkesworth 2011). A discount rate of 7% is assumed for all projects in this research, as shown in Table 7-3.

(2) Cost for false negative

The cost for misclassifying a positive sample means the cost for failing to detect a failed project. In a PPP project, the sponsors can commit equity and subordinated

debt (Yescombe 2002). In this research, the subordinated debt from the sponsors refers to the fees payable to consultants and arrangers by sponsors during a project finance deal, and it will be paid by the debt from the lenders or cash flows of the project if the project normally operates. However, the equity and subordinated debt should be paid after the senior debts from the lenders if the project goes into default. Therefore, the cost for misclassifying a positive sample will be the sum of equity and subordinated debt committed by the sponsors.

- For financial advisors, the fees payable include retainer fees or success fees. The feasibility study of a project needs to be conducted by the consultant, which would cause cost. When consultants' study leads to a successful conclusion, the success fee would be paid, which ranges from 0.5% to 1% of the debt value (Gatti 2013). In this research, the maximum value is used.
- Moreover, additional fees need to be paid to the lead arrangers, who pay the money to other co-arrangers. This fee is called the arranging fee, which is about 0.7% to 1% of the syndicated debt (Gatti 2013). In this research, the maximum value is used.

The success fee f_{sj} and arranging fee f_{aj} in a project j can be calculated by Eq. (7.7) and Eq. (7.8), respectively.

$$f_{sj} = D_j \times 1\% \quad (7.7)$$

$$f_{aj} = D_j \times 1\% \quad (7.8)$$

Finally, the cost for misclassifying a failed project can be calculated by Eq. (7.9).

$$C_{FN_j} = E_j + f_{sj} + f_{aj} \quad (7.9)$$

For instance, given a project with an investment size of 100 million dollars, the present value of the dividend at the end of the first year will be $d=0.15 \times 0.3 \times 100 \times 0.7 / (1+7\%) = 2.94$ and $d=0.12 \times 0.3 \times 100 \times 0.6 / (1+7\%) = 2.02$ million dollars under the project finance scheme and corporate finance scheme, respectively. Therefore, if a successful project is predicted to be failed, the opportunity cost for this year will be 0.92 million dollars. Moreover, the equity and subordinated debt committed by the sponsors are $100 \times 0.3 + 100 \times (1-0.3) \times 1\% + 100 \times (1-0.3) \times 1\% = 31.4$ million dollars. If the project ends as a failure and is predicted to be successful, the cost will be 31.4 million dollars.

7.2.3 Loss Function Development

In a binary classification problem, the loss function is a Cross-Entropy Loss. When the difference between the costs of various misclassification errors is neglected, the cross-entropy of one sample can be calculated by Eq. (7.10).

$$L(y, t) = -y \ln(t) - (1 - y) \ln(1 - t) \quad (7.10)$$

where y is the true label of the sample, which can be 0 or 1, and t is the predicted softmax probability of the sample, which can be obtained by Eq. (7.11).

$$t = p(x) = \frac{1}{1 + e^{-x}} \quad (7.11)$$

where x is the model output for a sample.

However, in the cost-sensitive classification problem, the loss function for a sample considering the asymmetric cost of misclassification can be calculated by Eq. (7.12).

$$L(y, t) = -y [C_{FN} \ln(t) + C_{TP} \ln(1 - t)] - (1 - y) [C_{TN} \ln(t) + C_{FP} \ln(1 - t)] \quad (7.12)$$

where C_{FN} , C_{TP} , C_{TN} , and C_{FP} denote the cost of FN , TP , TN , and FP , respectively.

Finally, the first-order derivative and the second-order derivative of Eq. (7.12) with respect to model output x should be obtained, which will be the final Gradient and Hessian. According to the chain rule, the first-order derivative can be denoted by Eq. (7.13).

$$\frac{\partial L(y, t)}{\partial x} = \frac{\partial L(y, t)}{\partial t} \cdot \frac{\partial t}{\partial x} \quad (7.13)$$

The first part of the Eq. (7.13) can be calculated by Eq. (7.14).

$$\begin{aligned} \frac{\partial L(y, t)}{\partial t} &= -\frac{C_{FN} y}{t} + \frac{C_{TP} y}{1 - t} - \frac{C_{TN} (1 - y)}{t} + \frac{C_{FP} (1 - y)}{1 - t} \\ &= \frac{C_{TP} y + C_{FP} (1 - y)}{1 - t} - \frac{C_{FN} y + C_{TN} (1 - y)}{t} \\ &= \frac{C_{TP} y t + C_{FP} (1 - y) t - [C_{FN} y + C_{TN} (1 - y)] \cdot (1 - t)}{(1 - t) \cdot t} \end{aligned} \quad (7.14)$$

The second part of the Eq. (7.13) can be calculated by Eq. (7.15).

$$\frac{\partial t}{\partial x} = e^{-x} t^2 \quad (7.15)$$

As a result, the first-order derivative of Eq. (7.12) with respect to model output x can be obtained by Eq. (7.16).

$$\begin{aligned}
\frac{\partial L(y,t)}{\partial x} &= \frac{\partial L(y,t)}{\partial t} \cdot \frac{\partial t}{\partial x} \\
&= \frac{C_{TP}yt + C_{FP}(1-y)t - [C_{FN}y + C_{TN}(1-y)] \cdot (1-t)}{(1-t) \cdot t} \cdot e^{-x} t^2 \\
&= \frac{C_{TP}yt + C_{FP}(1-y)t - [C_{FN}y + C_{TN}(1-y)] \cdot (1-t)}{1 - \frac{1}{1+e^{-x}}} \cdot e^{-x} \cdot \frac{1}{1+e^{-x}} \quad (7.16) \\
&= C_{TP}yt + C_{FP}(1-y)t - [C_{FN}y + C_{TN}(1-y)] \cdot (1-t) \\
&= [(C_{FN} + C_{TP} - C_{TN} - C_{FP})y + C_{TN} + C_{FP}] \cdot t + (C_{TN} - C_{FN})y - C_{TN}
\end{aligned}$$

The second-order derivative of Eq. (7.12) with respect to model output x can be denoted by Eq. (7.17).

$$\frac{\partial^2 L(y,t)}{\partial x^2} = \frac{\partial(\frac{\partial L(y,t)}{\partial x})}{\partial t} \cdot \frac{\partial t}{\partial x} \quad (7.17)$$

The first part of Eq. (7.17) can be calculated by Eq. (7.18).

$$\frac{\partial(\frac{\partial L(y,t)}{\partial x})}{\partial t} = (C_{FN} + C_{TP} - C_{TN} - C_{FP})y + C_{TN} + C_{FP} \quad (7.18)$$

Therefore, the second-order derivative of Eq. (7.12) with respect to model output x can be denoted by multiplying Eq. (7.18) and Eq. (7.15), as shown in Eq. (7.19).

$$\begin{aligned}
\frac{\partial^2 L(y,t)}{\partial x^2} &= \frac{\partial(\frac{\partial L(y,t)}{\partial x})}{\partial t} \cdot \frac{\partial t}{\partial x} \\
&= [(C_{FN} + C_{TP} - C_{TN} - C_{FP})y + C_{TN} + C_{FP}] \cdot e^{-x} t^2 \\
&= [(C_{FN} + C_{TP} - C_{TN} - C_{FP})y + C_{TN} + C_{FP}] \cdot \frac{e^{-x}}{(1+e^{-x})^2} \\
&= [(C_{FN} + C_{TP} - C_{TN} - C_{FP})y + C_{TN} + C_{FP}] \cdot t \cdot (1-t) \quad (7.19)
\end{aligned}$$

Finally, the cost function can be determined by the average loss of all samples, which can be calculated by Eq. (7.20).

$$C(Y, T) = \frac{1}{N} \cdot \sum_{i=0}^N L(y_i, t_i) \quad (7.20)$$

where Y is the set of the true label of all samples and T is the set of the predicted softmax probability of the sample. Besides, N is the number of samples in the data set. y_i and t_i is the true label and the predicted softmax probability of the i th sample.

7.2.4 Loss Function Implementation

Fig. 7.3 shows the principle of ECS-ML models and Fig. 7.4 shows the parameters and output of the objective function and evaluation function to customize a traditional ML model.

Fig. 7.3. The workflow of an ECS-ML model

As previously mentioned, unlike the conventional classification methods, the cost of misclassification errors will be taken into consideration by the loss function during the training process. After the model is trained by the training data set, it will be used to predict the label of new samples.

Fig. 7.4. Objective function and evaluation function

To make an ML model cost-sensitive, both the objective function and evaluation function are required to be customized, as shown in Fig. 7.4. The objective function, which can be a loss function, is any function that needs to be optimized during the

training, while the evaluation function is used to monitor the performance of the model when training a model. The objective function should receive two input variables named the prediction result and the true label of samples, based on which the gradient information in terms of first-order gradient and second-order gradient (Gradient and Hessian) will be provided by Eq. (7.16) and Eq. (7.19), respectively. Moreover, the evaluation function will receive the same input parameters as the objective function but the cost will be returned, as indicated by Eq. (7.20).

The proposed model is implemented by using Python codes. First, the objective function and the evaluation function are defined as independent functions. Then, the defined functions are used to replace the default values of the input parameters of the “train” function in “lightgbm” and “xgboost” libraries for LGB and XGB models, respectively.

7.2.5 Evaluation Metrics

The evaluation metrics mentioned in the last chapter are from the perspective of misclassifying errors, which are accuracy-oriented (Bahnsen et al. 2014). To evaluate the model from a financial perspective, a profit-oriented metric named cost-saving is proposed and adopted (Correa Bahnsen et al. 2015; Stolfo et al. 2000; Zelenkov 2019). The basic principle of this metric is that the cost-saving could be obtained by comparing the cost associated with misclassifications by the algorithm with the minimum cost of classifying all samples as one class, as shown in Eq. (7.21).

$$Cost_m(S) = \min\{Cost(f_0(S)), Cost(f_1(S))\} \quad (7.21)$$

where f_0 refers to a classifier that predicts all samples in set S as the class c_0 , while f_1 represents the classifier that predicts all samples in set S as the class c_1 .

Besides, the cost generated by applying a classifier f on the set S can be obtained by Eq. (7.22).

$$Cost(f(S)) = \sum_{i=1}^N \left(y_i (c_i C_{TP_i} + (1 - c_i) C_{FN_i}) + (1 - y_i) (c_i C_{FP_i} + (1 - c_i) C_{TN_i}) \right) \quad (7.22)$$

As a result, cost-saving can be obtained by Eq. (7.23).

$$Savings(f(S)) = \frac{Cost_m(S) - Cost(f(S))}{Cost_m(S)} \quad (7.23)$$

The values in the confusion matrix, precision, recall, and cost-saving will change as the models' threshold is modified. As mentioned in the last chapter, this threshold defines the probability at which a sample is labeled as positive (Baştanlar and Özuysal 2014). Besides, the determination of the threshold depends on the tasks and aims of the research.

7.3 Model Comparisons

7.3.1 Transportation Sector

Fig. 7.5 gives the project investment distribution for successful and failed projects in the transportation sector. Fig. 7.6 compares the ANN model, ECS ANN model, ECS LGB model, and the ECS XGB model from the perspective of the AUC score. The top bar in each figure is the best AUC obtained in the last chapter. Fig. 7.7 compares the cost-saving of different models on various data sets under the recall of 65.2%. Fig. 7.8 gives the ROC curve, PR curve, and the confusion matrix of the model with the highest cost-saving under the recall of 65.2%.

Fig. 7.5. Project investment distribution for successful and failed projects in the transportation sector

In the transportation sector, the investment of the failed projects is higher than that of the successful ones. It can be found from Fig. 7.5 that although the average investment size of the successful and failed projects is similar, the investment of 75% of the failed projects is larger than 97.05 million dollars, which is 2.84 times the

investment size of successful projects. This reflects that the larger transportation projects are more likely to encounter a failure.

From the perspective of the AUC score, the performance of the ECS-ML models is not always better than that of the conventional models. In Fig. 7.6, for the first and second data sets, the best model is the RF+SMOTE model, while the ECS LGB model and LGB+SMOTE model perform best for the third and the fourth data sets, respectively. The average AUC score of the ECS ANN model, ECS XGB model, and ECS LGB model on the four data sets is 73.65%, 72.35%, and 79.85%, respectively. That is to say, the ECS LGB model has better performance than other ECS-ML models, followed by the ECS ANN model. The average highest AUC score of the conventional models on the four data sets is 79.68%, which is slightly lower than 79.85%. Therefore, when it comes to the AUC score, there is no obvious increase in the performance after using ECS-ML models.

Fig. 7.6. AUC of ECS-ML models on different data sets in the transportation sector

From the perspective of cost-saving, the ECS-ML models produce higher scores in almost all data sets. The maximum cost of the test data set is 7274.4 million dollars, which corresponds to the case when all projects are predicted to be failed. The minimum cost of the data set is 2804.1 million dollars when all projects are predicted

as successful. Therefore, the negative cost-saving means that a large number of successful projects have been predicted as failed or the misclassified projects are with large investment size, causing large opportunity costs. Fig. 7.7 demonstrates that the ECS LGB model has the best performance in Data1, Data2, and Data3, although it is not always the best one from the perspective of the AUC score. For Data4, the best cost-saving is achieved when the RF+SMOTE model is adopted, closely followed by

Fig. 7.7. Cost-saving for different combinations in the transportation sector

the ECS LGB model. However, the cost-saving has been poorly obtained by the conventional models that have the highest AUC score on the four data sets. For

example, the cost-saving by the RF+SMOTE model on Data2 is 0.34, which ranks 7th among the fifteen combinations.

Fig. 7.8. ROC curve, PR curve, and confusion matrix for the selected model from the perspective of cost-saving in the transportation sector

The best model determined by the cost-saving is different from that confirmed by the F_1 score. It can be found from Fig. 7.7 that the highest cost-saving is found in Data2 when using the ECS LGB model. The cost-saving achieved is 0.74, which represents 2075.03 million dollars. As shown in Fig. 7.8, the FP of the best cost-effective model is higher than that of the best model by F_1 score, which is 28. That is to say, more successful projects have been predicted as failed. However, the cost-saving is 13.6% higher than that of the best model by F_1 score, which is 0.604 (Stack+UnderSampling+Data3 combination). In other words, 381.36 million dollars could be further saved by using the ECS-ML model. The difference could be explained by the fact that the error for FP and FN is not equal, which is, however, assumed to be the same in the conventional metrics.

7.3.2 Water & Sewerage Sector

Fig. 7.9 gives the project investment distribution for successful and failed projects in the W&S sector. Fig. 7.10 compares the ANN model, ECS ANN model, ECS LGB model, and the ECS XGB model from the perspective of the AUC score. The top bar in each figure is the best AUC obtained in the last chapter. Fig. 7.11 compares the cost-saving of different models on various data sets under the recall of 66.7%. Besides, Fig. 7.12 gives the ROC curve, PR curve, and the confusion matrix of the model with the highest cost-saving under the recall of 66.7%.

Fig. 7.9. Project investment distribution for successful and failed projects in the W&S sector

The investment of the failed projects is much higher than that of the successful ones for the W&S sector. Fig. 7.9 shows that the average investment of failed projects is 426.45 million dollars, which is 5 times more than it is for successful projects. Besides, the investment of 75% of the failed projects is larger than 18.6 million dollars, which is 2.74 times the investment size of successful projects. Although the

Fig. 7.10. AUC of ECS-ML models on different data sets in the W&S sector

investment size in the W&S sector is much smaller than that in the transportation sector, it also shows the tendency that the larger W&S projects have a higher probability to fail.

Fig. 7.11. Cost-saving for different combinations in the W&S sector

From the perspective of the AUC score, the performance of the ECS-ML models is always lower than that of the best conventional models. In Fig. 7.10, the RF model has the best performance for all data sets. For the first, third, and fourth data sets, the best combination is the RF+Undersampling combination, while the RF+SMOTE combination works best for the remaining data sets. The average AUC score of the

ECS ANN model, ECS XGB model, and ECS LGB model on the four data sets is 81.13%, 66.2%, and 72.48%, respectively. That is to say, the ECS ANN model has better performance than other ECS-ML models. The average highest AUC score of the conventional models on the four data sets is 84.43%, which is much higher than 81.13%. This also verifies the conclusion that the conventional models have higher AUC scores than ECS-ML models.

Like the transportation sector, the ECS-ML models produce higher cost-saving in almost all data sets in the W&S sector. The maximum cost of the test data set is 847.5 million dollars, which corresponds to the case when all projects are predicted to be failed. The minimum cost of the data set is 552.5 million dollars when all projects are predicted as successful. Fig. 7.11 demonstrates that the ECS ANN model performs the best in Data1, the XGB+Undersampling combination has the best performance in Data2, and the ECS XGB model has the best result in Data3 and Data4.

Fig. 7.12. ROC curve, PR curve, and confusion matrix for the selected model from the perspective of cost-saving in the W&S sector

The best model determined by the cost-saving is different from that confirmed by the F_1 score in the W&S sector. It can be found from Fig. 7.11 that the highest cost-saving is found in Data4 when using the ECS XGB model. The cost-saving achieved is 0.741, which represents 409.4 million dollars. Fig. 7.12 shows that the FP is higher than that of the best model by F_1 score, which is 18. That is to say, more successful projects have been predicted as failed. However, the cost-saving is 7.8% higher than that of the best model by F_1 score, which is 0.663 (XGB+UnderSampling+Data2 combination). In other words, 43.1 million dollars could be further saved by using the ECS-ML model.

7.3.3 Energy Sector

Fig. 7.13 gives the project investment distribution for successful and failed projects in the energy sector. Fig. 7.14 compares the ANN model, cost-sensitive ANN model, cost-sensitive LGB model, and the cost-sensitive XGB model from the perspective of the AUC score. The top bar in each figure is the best AUC obtained in the last chapter. Fig. 7.15 compares the cost-saving of different models on various data sets under the recall of 62.5%. Besides, Fig. 7.16 gives the ROC curve, PR curve, and the confusion matrix of the model with the highest cost-saving under the recall of 62.5%.

Fig. 7.13. Project investment distribution for successful and failed projects in the energy sector

In the energy sector, the investment size of the failed projects is also much higher than that of the successful ones for the energy sector. The average investment of failed projects is 309.78 million dollars, which is 89.75 million dollars more than that of successful projects. Besides, Fig. 7.13 shows that the investment of 75% of the failed projects is larger than 66.45 million dollars, which is 2.75 times the investment size of successful projects. The investment size in the energy sector is larger than that in the transportation sector, and the larger energy projects have a higher probability to fail.

ECS-ML models always have lower AUC scores than the best conventional model in the energy sector. As shown in Fig. 7.14, the average AUC score of the ECS ANN model, ECS XGB model, and ECS LGB model on the three data sets is 73.2%, 76.2%, and 81.8%, respectively. This value for the best traditional model (XGB+SMOTE model) is 87.9%, much higher than 81.8%. Moreover, the ECS LGB model has better

performance than other ECS-ML models, with an improvement of 8.6% in the AUC score.

Fig. 7.14. AUC for cost-sensitive models in the energy sector

The highest cost-saving has been found in the proposed ECS-ML models. The minimum cost of the data set is 1911.13 million dollars, which corresponds to the case when all projects are predicted as successful. The maximum cost of the test data set is 11001.99 million dollars, which happens when all projects are predicted to be failed. Therefore, the negative cost-saving means that a large number of successful projects have been predicted as failed or the misclassified projects are with large investment size, causing large opportunity costs. Fig. 7.15 demonstrates that the RF+SMOTE combination has the best performance in Data1 and Data2, and the ECS LGB model has the best performance in Data3. The best cost-saving in Data3 is 0.165 higher than that in Data2 and 0.253 higher than that in Data1.

The best model determined by cost-saving and F_1 score is different. It can be found from Fig. 7.15 that the highest cost-saving is found in Data3 when using the ECS LGB model. The cost-saving achieved is 0.438, representing 837.07 million dollars. Moreover, models with a higher AUC do not necessarily generate better cost-saving (Xia et al. 2017). For example, the XGB+SMOTE combination has the highest AUC

score of 87.2% for Data1. However, its cost-saving only ranks fourth. Fig. 7.16 demonstrates that the false positive of the best ECS-ML model is lower than that of the best model (KNN+SMOTE+Data3 combination) by F_1 score, which is 35. As a result, the accuracy has increased to 92.7%. Furthermore, the cost-saving is also improved by 0.3, with an initial value of 0.138. In other words, 573.34 million dollars could be further saved by using the ECS LGB model.

Fig. 7.15. Cost-saving for different combinations in the energy sector

Fig. 7.16. ROC curve, PR curve, and confusion matrix for the selected model from the perspective of cost-saving

7.4 Sensitivity Analysis

To provide a guideline for PPP sponsors in selecting the proper model, the sensitivity analysis has been conducted to obtain the maximum cost-saving by comparing the models under various recalls obtained by adjusting the threshold of the model.

7.4.1 Transportation Sector

Fig. 7.17 gives the cost-saving for models in the four data sets for the transportation sector, where the circle and square denote the models with SMOTE technique and random undersampling technique, respectively, and the triangle denotes the ECS-ML model. Besides, the black line in each figure represents the model with the best cost-saving. Fig. 7.18 gives the confusion matrix for the best model by F_1 score and cost-saving under the recalls of 60.9%, 65.2%, and 69.6%, respectively, where (a)-(c) are from the perspective of F_1 score, and (d)-(f) are from the perspective of cost-saving. Fig. 7.17 shows that the ECS LGB model is the best combination under various recalls in Data1, Data2, and Data3. The maximum cost-saving is 0.74, which is provided by the ECS LGB+Data2 combination under the recall of 65.2% (15 out of 23 failed projects have been detected). In other words, 2075.03 million dollars have been saved. For Data4, the ECS LGB model also achieved the largest cost-saving under the recall of 60.9%. From a holistic view, the ECS-ML models perform better than conventional models from the financial perspective. Therefore, when predicting the contract failure of a PPP transportation project, the ECS-ML models are recommended.

Fig. 7.17. Cost-saving under different recalls in various data sets in the transportation sector

For the transportation sector, the ECS-ML models could improve the cost-saving but decrease the F_1 score. Fig. 7.17 shows that the cost-saving is larger in Data2, indicating that newly proposed factors have little influence on the cost-saving of the model in the transportation sector. In Fig. 7.18, the precision of the model with the largest F_1 score is always larger than that of the model with the best cost-saving under various recalls. The improvement in the cost-saving under the three recalls is 0.11, 0.136, and 0.28, respectively. Overall, when a sponsor is pursuing a high recall, the best option is the Stack+SMOTE+Data2 combination under the recall of 69.6%, with an F_1 score of 40.5%. When the cost-saving is on the top of their agenda, the best option is the ECS LGB+Data2 combination under the recall of 65.2%, meaning an F_1

score of 39.0% and the cost-saving of 0.74. Finally, when both the F_1 score and the cost-saving are important, the best combination should be the Stack+Under+Data3 combination under the recall of 65.2%, with a pretty high F_1 score of 45.4% and a cost-saving of 0.604.

Fig. 7.18. The confusion matrix of the best model under various recalls in the transportation sector

7.4.2 Water & Sewerage Sector

Fig. 7.19 gives the cost-saving for models in three data sets for the W&S sector, where the circle, square, and triangle denote the models with SMOTE technique, undersampling technique, and ECS-ML models, respectively, and the black line in each figure represents the model with the best cost-saving. Fig. 7.20 gives the confusion matrix for the best model by the F_1 score and cost-saving under the recalls of 58.3%, 66.7%, and 75.0%, respectively, where (a)-(c) are from the perspective of F_1 score, and (d)-(f) are from the perspective of cost-saving.

Fig. 7.19. Cost-saving under different recalls in various data sets in the W&S sector

Fig. 7.19 shows that the ECS-ML models work better on Data3 and Data4, while the traditional models perform better on Data1 and Data2. Unlike the transportation sector, the undersampling technique has a similar performance as the SMOTE technique in the W&S sector. The maximum cost-saving is 0.774, which is provided by the LGB+Data3 combination under the recall of 58.3% (7 out of 12 failed projects have been detected). More specifically, 427.64 million dollars have been saved.

In this sector, the ECS-ML model is not always performing better than traditional models in cost-saving. Fig. 7.20 shows that the cost-saving is larger in Data1 and Data4, which indicates that model performance is improved by introducing the PPP experience levels of a country and importance indicators. Overall, when a sponsor is

perusing the high recall, the XGB+Under+Data2 combination under the recall of 75% is the best option. It has achieved an F_1 score of 43.9%. When the cost-saving is on the top of their agenda, the best option is the LGB+SMOTE+Data3 combination under the recall of 58.3%, meaning the cost-saving of 0.774. Finally, when both the F_1 score and the cost-saving are important, the best option is the ECS XGB+Data4 combination, which has achieved an F_1 score of 31.4% and a cost-saving of 0.741.

Fig. 7.20. The confusion matrix of the best model under various recalls in the W&S sector

7.4.3 Energy Sector

Fig. 7.21 gives the cost-saving for models in three data sets for the energy sector, where the circle, square, and triangle denote the models with SMOTE technique, undersampling technique, and ECS-ML models, respectively, and the black line in each figure represents the model with the best cost-saving. Fig. 7.22 gives the confusion matrix for the best model from the viewpoint of the F_1 score and cost-saving under the recalls of 56.3%, 62.5%, and 68.8%, respectively, where (a)-(c) are from the perspective of F_1 score, and (d)-(f) are from the perspective of cost-saving.

Fig. 7.21. Cost-saving under different recalls in various data sets in the energy sector

Fig. 7.21 shows that the RF+SMOTE combination is the best combination under various recalls in Data1 and Data2. However, it is not the model achieving the largest cost-saving. The maximum cost-saving is 0.452, which is provided by the ECS LGB+Data3 combination under the recall of 56.3% (9 out of 16 failed projects have been detected). More specifically, 863.83 million dollars have been saved. For Data3 and Data4, the ECS LGB model and LGB+SMOTE model perform better than other models, respectively. From a holistic view, the models using SMOTE technique can achieve larger cost-saving than the model with the random undersampling technique. Therefore, when predicting the contract failure of a PPP energy project using traditional algorithms, the SMOTE technique is recommended.

Fig. 7.22. The confusion matrix of the best model under various recalls in the energy sector

In general, the ECS-ML model could improve both the F_1 score and cost-saving in the energy sector. Fig. 7.21 shows that the cost-saving is larger in Data3, which indicates that model performance is improved by introducing the PPP experience levels of a country. Moreover, in Fig. 7.22, the precision and cost-saving of the model have been improved by ECS-ML models under the recall of 56.3% and 62.5%. Under the recall of 68.8%, the cost-saving has raised to 0.26 from 0.244 although the precision has decreased. The reason is that projects with high investments, meaning higher misclassification costs, are more likely to be correctly picked by the ECS-ML model. Overall, when a sponsor is perusing the high recall, the best option is the Stack+SMOTE+Data3 combination under the recall of 68.8%, with a relatively high F_1 score of 33.9%. When the cost-saving is on the top of their agenda, the best option is the ECS LGB+Data3 combination under the recall of 56.3%, meaning an F_1 score of 32.7% and the cost-saving of 0.453. Finally, when both the F_1 score and the cost-saving are important, the best option is the ECS LGB+Data3 combination under the recall of 62.5%, achieving a cost scoring of 0.438 and an F_1 score of 34.5%.

7.4.4 Guideline on Model Selection

Table 7-4 gives the guideline of model selection based on various requirements. “Recall” and “Cost-saving” represent various selection criteria, while “ F_1 score and cost-saving” represent that F_1 score and cost-saving will be considered at the same time. “Parameter” denotes the value of the parameters of the selected model. Moreover, the unit of the “money saved” is million dollars.

Table 7-4 Model selection criteria for various sectors

Sector	Parameter	Recall	Cost-saving	F_1 score and cost-saving
Transportation sector	model	Stack+SMOTE	ECS LGB	Stack+Under
	data set	Data2	Data2	Data3
	recall	69.6%	65.2%	65.2%
	F_1 score	40.5%	39.0%	45.4%
	cost-saving	0.418	0.740	0.604
	money saved	1172.1	2075.0	1693.7
W&S sector	model	XGB+Under	LGB+SMOTE	ECS XGB
	data set	Data2	Data3	Data4
	recall	75%	58.3%	66.7%
	F_1 score	43.9%	40.0%	31.4%
	cost-saving	0.687	0.774	0.741
	money saved	379.6	427.6	409.4
Energy sector	model	Stack+SMOTE	ECS LGB	ECS LGB
	data set	Data3	Data3	Data3
	recall	68.8%	56.3%	62.5%
	F_1 score	33.9%	32.7%	34.5%
	cost-saving	0.244	0.453	0.438
	money saved	466.3	865.7	837.1

It can be seen from Table 7-4 that the best model varies with selection criteria and the PPP sector. When selecting a model, the users need to confirm the required criteria first. Then, the model, including ML model and data balancing techniques if available, as well as data set should be selected. Generally speaking, the ECS-ML models have improved the cost-saving to a large extent. Besides, by introducing the factors of the PPP experience levels and importance of the countries, the performance of the model has been improved.

7.5 Summary

Predicting the contract failure of a PPP project is challenging partly because of the imbalance of the data sets and the disadvantages of current ML models. To help the sponsors to make strategic decisions when selecting a PPP project, this chapter applied the ECS algorithms in PPP contract failure prediction from a financial perspective. In this research, the cost matrix for PPP projects has been proposed by using the opportunity cost for the false-positive samples and equity loss for the false-negative samples. Besides, the performance of various models is compared from the accuracy-oriented and profit-oriented metrics. The results could provide a guideline on selecting the appropriate models that are the most accurate or cost-effective. The conclusions of this research are:

1. The proposed cost matrix for the PPP projects is effective. Reasonable results have been obtained by treating the difference between the profits of supporting a project using project finance and corporate finance as the cost of misclassifying a successful project and the equity loss as the cost for developing a failed project.
2. The ECS-ML model may improve the cost-saving. For the transportation sector, W&S sector, and energy sector, the largest cost-saving is 0.74, 0.774, and 0.452, respectively. They are achieved by the ECS LGB model, LGB+SMOTE combination, and ECS LGB model, respectively.
3. The traditional models could achieve a better AUC score. For the transportation sector, the average AUC score of ECS-ML models is slightly higher than that of the traditional models. For W&S and energy sectors, the average AUC score across the four data sets is much higher in traditional models. However, the ECS-ML models have higher cost-saving in the transportation and energy sectors. That is to say, the model with a larger AUC score does not indicate a cost-effective model.
4. The best model varies with sectors. The guideline in selecting the most appropriate machine learning model for each sector has been given from the perspective of statistical and profit perspectives.

Chapter 8 Conclusions and Recommendations

This chapter gives the main findings and contributions of the thesis, followed by the limitations and recommendations for future works.

8.1 Conclusions of Research

Three main objectives of this research have been set in Chapter 1. The major findings concerning each objective could be found below.

- a. Quantifying developing countries' PPP experience levels.

To achieve this objective, a hybrid Bayesian hierarchical model is developed to quantify countries' PPP experience levels based on the idea of change point detection. First, the PPP experience of a country is quantified based on the number of PPP projects that it has developed in a specific year. Second, the World Bank's PPI database is cleaned and analyzed, and the concept of PPP experience level is proposed. Finally, the Bayesian hierarchical model is developed to detect change points in the contract failure rate, and the PPP experience corresponding to these change points is thought to be the bounding of the PPP experience level. Some conclusions are obtained: 1) the numbers of the experience level of the energy sector, transportation sector, and W&S sector are 4, 5, and 5, respectively, 2) the PPP experience level is not evenly distributed around the world and most developing countries do not have enough experience to manage a PPP project. For example, countries such as China and the Philippines in the East Asia and Pacific (EAP) region have higher PPP experience than those in other regions, 3) the same country may have different PPP experience levels in different sectors, and 4) the learning rate varies with the infrastructure sector. For example, gaining experience in the transportation sector is easier than in other sectors. These results reveal the distribution of PPP experience levels on earth, which could help private investors to choose the right investment direction. Details are explained in Chapter 4.

- b. Quantifying countries' importance in transferring PPP knowledge around the world.

To achieve this objective, the social network analysis approach is adopted to analyze the collaborative relationships among different countries since 1990. First, a series of

networks have been established to denote the participation of foreign countries in the project of a host country, where the PPP knowledge is assumed to be transferred from the foreign countries to the host countries. Second, the macro- and micro-level metrics, such as centrality and PageRank, are adopted to quantify the importance of different countries in transferring PPP knowledge. Finally, the PPP knowledge transfer paths among the countries in a region and between different regions are revealed. Some conclusions are obtained: 1) developing countries are more likely to involve more foreign countries in the same PPP project, 2) it is also revealed that the top-ranked countries in knowledge transfer are changing with time although some countries are always pretty active, such as the US and UK, 3) some less knowledgeable countries such as Peru and Brazil can also have high importance as these countries have involved a lot of developed countries in their projects, 4) important countries in one sector are more likely to be vital in the other one. For example, China and France are important knowledge sources in the transportation and ICT sectors, and 5) most countries are more likely to be involved in projects near their borders. For example, 53.8% of foreign PPP projects by Japan, and 72.0% by Singapore are in the EAP region. This part provides a series of indexes for the importance of a country in transferring PPP knowledge and reveals the knowledge transfer paths, which could help the project sponsors to choose right partners. Details are explained in Chapter 5.

- c. Combining the previously proposed factors with other existing project-specific and country-specific variables to predict the final status of a PPP contract using both traditional ML models and ECS-ML models.

To achieve this objective, the PPP contract failure is predicted by using both the traditional machine learning models and the proposed example-dependent cost-sensitive (ECS-ML) models, and the failure factors of a PPP contract are detected from a quantitative perspective. First, twenty-one project-specific factors and twenty country-specific factors are extracted from the PPI database, WDI database, and WGI database. Second, four data sets have been established by introducing the newly proposed factors from Chapter 4 and Chapter 5. Third, the traditional machine learning models are adopted to predict contract failure from a statistical perspective. Fourth, the primary failure factors are detected and discussed. Fifth, the concept of

cost matrix and cost savings for PPP projects are proposed. Finally, an ECS-ML model is proposed to predict contract failure from a financial perspective. Some conclusions are obtained: 1) the top 15 failure factors for the transportation sector, W&S sector, and energy sector are picked according to the results of PCA, 2) the ECS-ML model may improve the cost-saving of the results, although the traditional models perform better in the AUC score, and 3) the most precise model is not necessarily the most cost-effective. This part provides a useful guideline for other scholars and practitioners in selecting the machine learning models to predict the outcome of a PPP project. Details are explained in Chapter 6 and Chapter 7.

Finally, the conclusion on the list of top priorities is that all the results in this thesis could be good references for establishing policies. Both governments in developing and developed countries could establish their policies based on the results in this thesis. Some policy suggestions are given as below: 1) the domestic companies could be encouraged to collaborate with the foreign companies in their neighboring countries in the PPP domain, 2) the process of PPP contract failure prediction should be carried out during the process of the planning phase to achieve the value for money as much as possible, and 3) the power of the government in a PPP project in the water & sewerage sector should be strong enough, which can be regulated in the policy by restricting the rights of the private sector and emphasizing the step-in right of the government.

8.2 Main Contributions

By solving the detected problems in the current literature and achieving the objectives of this research, the study has its theoretical and practical contributions. It can contribute to the engineering management and PPP domains in several aspects.

- 1) Rather than using qualitative methods, this research focuses on quantitative methods. The quantified PPP experience levels considering the uncertainties are expected to provide support for private investors in selecting investment directions. At the same time, the indexes for the importance of a country in transferring PPP knowledge could guide the PPP sponsors in selecting appropriate partners. These indexes are more intuitive and standard and have the potential to be further optimized and promoted.

- 2) The failure factors of the PPP projects have been obtained, this could lead the government to consider these factors when making the policies to guarantee the smooth operation of a PPP project and development of PPPs in developing countries.
- 3) The fuzzy model of a Bayesian hierarchical model and binary segmentation method has been proposed to detect the change points. This is useable not only for detecting PPP experience levels but also for other relevant problems.
- 4) The proposed example-dependent cost-sensitive machine learning model could relieve the data imbalance in the construction domain especially the PPP domain. Predicting the outcome of a PPP project could mitigate projects' risks, attract more investment from private investors and reduce the financing cost, which is useful in delivering the best value for money. By saving the cost of the project, the burden of the government could also be decreased, especially in poor countries where government guarantees are usually required to enhance the bankability of the PPP project.

Overall, this research would provide other scholars with a systematic understanding of the cooperation among different countries in the PPP domain over time and the guidance for PPP developers to establish a competitive team for the aim of efficient knowledge transfer. It could also contribute to the transformation of managerial approaches given that data-driven approach and big data value have been realized by an increasingly large number of researchers.

8.3 Limitations and Recommendations for Future Works

However, there are some limitations to this thesis. First, the PPP experience may also be influenced by other factors, such as the investment scale or complexity of the project. These factors are, however, not considered when quantifying the PPP experience levels in this study. Second, foreign countries and their roles in PPP projects are manually extracted from the PPI database. The data for establishing the social network may contain some errors due to not only data gaps in the PPI database but also mistakes made during the data extraction process. Third, the knowledge transfer mechanisms have been simplified, and the knowledge transfer achieved by different roles is not considered. Fourth, knowledge transfer from the host countries

to foreign countries in the same project has been neglected. Fifth, the cost matrix is assumed to be the same for different PPP sectors. Sixth, the cost caused by the bad reputation when a project fails is not considered in the cost matrix. Finally, the PPI database only includes large projects. The projects in health, education, prisons, and simple government buildings have been excluded (Loxley 2013), which may influence the importance of failure factors.

In future work, more work could be carried to improve or expand the current works. First, the natural language processing (NLP) method will be used to analyze the unstructured information in the PPI database to guarantee the accuracy of the information extraction. Second, countries' ability to absorb knowledge from other countries will be examined to evaluate the extent of knowledge transfer. Third, the global PPP project market will be analyzed to obtain cooperation among different countries from a new perspective. Finally, the indexes proposed in this thesis could be further optimized and promoted.

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