# Application of Crowdsourcing to Resolve Ambiguity Involved in Contracting

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Abstract:

There is commonly a level of ambiguity involved in buyer supplier relationships. This causes misunderstanding and consequently receiving unsatisfactory products. Avoiding ambiguity and fuzziness in the determination of buyer requirements is crucial. To date insufficient studies have been undertaken that investigate this aspect of the procurement process. A number of previous studies focus on requirement specification and elicitation. However, these have a software engineering focus. This issue in the procurement process and proposes has been investigated and an integrated framework using intelligent techniques have been proposed. The research contributes to the contract theory by leveraging intelligent techniques in automated or semi-automated contract monitoring.

Keywords: Crowdsourcing; Procurement process; Ambiguity

## Introduction

The traditional form of contracting considers the resources and processes utilized by the provider as the basis of the payment. In contrast, todays common form of contracting, sometimes labelled Performance Based Contracting (PBC) (Glas, Henne, & Essig, 2018), has been developed and gained increasing popularity (Wang, Qing, Wang, & Li, 2018).

In today's contracts, the buyer usually is not involved in monitoring the production process; instead, the buyer defines a set of requirements and specifications for the product or service and then the onus is on the contractor to provide the product or service that meets the requirements (Sharma & Pandey, 2018). The success of the procurement process depends on not only the measurability of the performance, but also the definition of unambiguous requirements (Dick, Hull, & Jackson, 2017). Ambiguity in defining requirements is a critical issue that can have serious consequences (Dick et al., 2017). The consequences may start immediately after signing the contract and may last until the end of the product life cycle.

Information asymmetry can sometimes be the reason for the existence of ambiguity in a contract. The asymmetry is concerned with the information that either side of a contract, buyer or provider, is not aware of while the other party has some knowledge about it (Manes & Tchetchik, 2018). Both parties have interest in keeping the contract vague, for different reasons (Asadabadi, Saberi, & Chang, 2017). The main aim of this study is to propose a requirement specification approach which involves methods such as soft computing techniques, Natural Language Processing (NLP), and crowdsourcing that will help to further clarify the requirements and responsibilities of both supplier and buyer at the time of contract signature.

The remainder of this paper is as follows. After this brief introduction, there is an investigation of the most relevant papers. Then, the research method that integrates NLP, crowdsourcing, and fuzzy logic is explained.

## Literature Review

Today's common forms of contracting methods are referred to as performance or outcome-based contracts (Selviaridis & Wynstra, 2015). In contracts of this type, a set of requirements is defined by the buyer for the acquisition and procurement process of products or services (Visnjic, Jovanovic, Neely, & Engwall, 2017). The buyer focuses on the outcome (Omizzolo Lazzarotto, Borchardt, Pereira, & Almeida, 2014), rather than materials, resources, or processes utilized (Selviaridis & Norrman, 2014). With this approach, it is expected that the quality is improved and a better outcome is achieved (Martin,

2015; Sultana, Rahman, & Chowdhury, 2013) while decreasing the monitoring costs (Griffith & Zhao, 2015; Lu, 2014, 2016).

Although some studies question the effectiveness of new methods of contracting (Gruneberg, Hughes, & Ancell, 2007; Ssengooba, McPake, & Palmer, 2012), it is acknowledged that there is increased interest in applying this method. Considering this interest, even researchers questioning the method recommend further studies in order to improve the effectiveness of the methods of contracting (Azemati et al., 2013; Ssengooba et al., 2012). Lu (2014) relates the infectiveness of contracting with the inherent uncertainty in this approach which creates a space for provider opportunism. Thus, a qualitative approach was applied by Lu (2014) in a public service provisioning to examine the effectiveness of outcome-based contracting with regard to the service outcome from the provider's perspective. Two years later, Lu (2016) did a quasi-experiment on a case study to further "*elucidate the effectiveness of PBC*" and continued to emphasize on taking caution while applying contracting methods such as PBC.

One of the shortcomings of these new methods of contracting is the unwanted creation of a space for provider to take advantage of the contract. This can sometimes be addressed by using a simple approach to measure performance if the requirements are clear. For example, the provider can service easy to satisfy customers (cream skimming) and ignore the hard to service customers and so obtain a higher payment based on the higher number of served customers (Koning & Heinrich, 2013). Koning & Heinrich (2013) deal with this issue proposing a categorization of jobs from easy to hard, and consider a pre-assigning job system to the provider. They then determine the fraction of service for each group as well as a job replacement rate to monitor the cream skimming of their performance to address the issue. But the case is not always this easy. If requirements lack clarity, the providers are able to meet the requirements only from their own point of view and based on their own interpretations. This makes the provider be able to prematurely claim for the relevant payments. Considering such consequences, the buyer may think that following an outcome-based approach is a mistake, preferring instead traditional forms of contracting in the future contracts. Clearly, it becomes even more important for any buyer to be able to determine, in exact terms, what they want.

One of the issues hindering the specific determination of requirements is information asymmetry, particularly because it prompts opportunistic behaviour. Opportunistic behaviour (Sumo, Valk, Weele, & Duysters, 2016) and uncertainty in the buyer supplier relationship is dealt with in Agency Theory (Duren, Dorée, & Voordijk, 2015; Eisenhardt, 1989; Voordijk, 2015). These issues arise where there is information asymmetry created when the parties involved in an outsourcing agreement do not have equal access to the same amount or quality of information (McCarthy, Silvestre, & Kietzmann, 2013). Eliminating information asymmetry results in effective procurement decisions based on the perfect information. However, in reality, neither buyer nor supplier is interested in sharing information in so far as information asymmetry is considered as a power (Omizzolo Lazzarotto et al., 2014). Sharing information to help the process of information elicitation, future significant financial advantage out of the relationship (Hooper, 2008; McCarthy et al., 2013)

In summary, these new methods of contracting have gained increasing popularity (Sumo, van der Valk, van Weele, & Bode, 2014) especially in the public sector (Koning & Heinrich, 2013; LÊgreid, 2017). This popularity, resulting from the effectiveness of the method, has encouraged governments (Selviaridis & Wynstra, 2015) to make outcome-based approaches compulsory or at least preferred in government contracting (Martin, 2015; Pozzetti & Clark, 2015). But still, contracting the future performance is a challenging issue (Mouzas, 2016). Although the benefits of outcome based contracting have been acknowledged in several studies, there are examples of governments withdrawing from outcome-based contracting and returning to traditional contracting methods (Koning & Heinrich, 2013). This could be expected since outcome based contracting methods, such as PBC, are uncertain in nature and have the potential to be subject to contractor opportunism (Lu, 2014). Contractor opportunism can be avoided by undertaking requirement specification early in contracts.

## Methodology

The framework consists of three main steps. First is the NLP that identifies the ambiguous words in the contract. Second is to recognize which words can be addressed which is by crowdsourcing. Third is clarifying those words using fuzzy logic.

**Natural Language Processing (NLP)**

The onus of identifying sources of ambiguity which can result in future negotiations and arguments between supplier and buyer is on NLP. Considering the volume of governments' contracts, it is very time consuming and costly to employ experts to go through each sentence of every contract and determine whether a part would cause misinterpretation or has the potential to be misused to deliver defective products. This motivates applying semi-automated techniques. The method involves following a set of rules, scanning the text, and finding and highlighting any ambiguous terms and words.

While all ambiguities in contracts cannot be recognized following a set of rules, we could identify text characteristics that have a high potential for creating ambiguities. In doing so, we learnt that the contract should be kept clear. As much as possible the text should avoid from using passive verbs such as *should be linked, need to be associated with,* predicates such as *slow performing, rapid accomplishment, quality products,* quantifiers such as *several jobs, few inputs, temporal breakage,* and modifiers such as *less, smarter, softer*. Although this paper aims at resolving ambiguities of contracts in the procurement process, previous studies in software engineering lead us to a comprehensive categorization of terms that are ambiguous. A list of such terms is included in ISO/IEEE/IEC 29148. The table below shows two categories that are clarified by this study: the rest are left for future studies.

**Table 1: Types of ambiguous terms**

| | |
|---|---|
| Superlatives (such as 'best') | Not in the scope |
| Subjective language (such as 'user friendly') | Not in the scope |
| Vague pronouns (such as 'they') | Not in the scope |
| Ambiguous adverbs and adjectives (such as 'significantly') | **This is clarified** |
| Open-ended, non-verifiable terms ('not limited to') | Not in the scope |
| Comparative phrases (such as 'smaller than') | **This is clarified** |
| Loopholes (such as 'if applicable) | Not in the scope |
| Negative statements (such as 'not to be performed) | Not in the scope |

These can be highlighted applying NLP techniques on a platform such as ConQAT (https://www.cqse.eu/en/products/conqat/overview/ ). One of the NLP techniques that is used to identify parts of sentences is Part of Speech (POS) tagging. POS identifies the components such as nouns, verbs, adverbs, and adjectives. POS can also be used for further analysis of the text, for example whether the identified adjective is superlative or comparative (see Stanford Parser: http://nlp.stanford.edu:8080/parser/). Stemming and lemmatization techniques are used to return the common and base forms of a word. For example

company's, companies, companies'⟹ company

This technique is used to compare words that are used in a contract with the database of the saved ambiguous terms in the system (the database becomes a comprehend glossary of ambiguous examples by passing time). Researchers are currently developing techniques that would enable highlighting such ambiguities more efficiently (Femmer, Fernández, Wagner, & Eder, 2017; Rosadini et al., 2017; Rossanez & Carvalho, 2016). But, what is missing is how the identified ambiguities should be addressed. Contract ambiguities in software engineering is relatively new area of concern and it has not yet been studied in government procurement projects. This study creates a link between the output of NLP to fuzzy set theory, a link which helps designing a framework to resolve the issues. In the next section, how

crowdsourcing power is leveraged in contract monitoring to enhance NLP procedure is explained.




Figure 1

**Crowdsourcing**

Although automatic approaches have previously been examined to find defects in requirement specification in software engineering (Falessi, Cantone, & Canfora, 2013; Gleich, Creighton, & Kof, 2010; Juergens et al., 2010; Kof, 2007) considering the complexity of the process and performance based contracting (Schoenmaker & de Bruijn, 2016), it does not seem as a means of empowering a framework to detect ambiguities automatically with no errors (Femmer et al., 2014). Such a framework requires expert supervision. Experts modify the NLP outputs by accepting or rejecting the existence of ambiguity in the highlighted phrases. Using crowdsourcing techniques (Hossain & Kauranen, 2015) crowd of experts is enlisted in the crowdsourcing system to help solving problems which are difficult for computer to solve (Michelucci & Dickinson, 2016). Techniques in Dumpster–Shafer theory, and similar techniques can be applied to ensure that the experts' opinions are employed in the process. The experts will be educated about the text related errors of the product, after the product is delivered. Therefore, two monitoring schemes in this work are considered: the online and post-delivery monitoring. These two monitoring schemes are explained as follows:

**Online monitoring**

NLP in this study benefits from human modifications. The output is modified by the user and the system starts learning from the experts' modifications as shown in Fig. 1. Terms and phrases that are highlighted in NLP receive a degree of certainty. This degree increases with regard to the times that have been highlighted and approved by the experts. Gradually the experts can be asked to check only those terms which are identified with low certainty, for example those with certainty level lower that $\lambda$ ($0 \leq \lambda \leq 1$). This means that, with the passage of time and more usage of NLP, the role of the experts $R_{EXP}$ gradually decreases.

A data base is considered for NLP. This data base is fed by the approvals or rejections received from experts. The certainty level is computed based on how often that phrase had been previously approved by experts. If a sentence or a phrase is used in the current contract that previously has always been approved by experts, it can be considered as ambiguity with high degree of certainty and does not require experts' opinions.

The expert's role is computed as follows:

$$R_{EXP}^{i} = \frac{\#Expert's\ adjustments\ in\ i^{th}\ contract}{\#\ Highlighted\ Phrases\ in\ i^{th}\ contract}$$

$$0 \leq R_{EXP}^{i} \leq 1$$

If $R_{EXP}^{i}$ stands for the role of experts in the $i^{th}$ contract, we expect the following equation to be true.

$$\text{Lim } R_{EXP}^{n} = 0 \text{ ,}$$

$$n \rightarrow \infty$$

**Fuzzy logic**

Of the ambiguities highlighted by NLP and the experts (note: the role of the expert should gradually decrease), some can be addressed using fuzzy sets. Using fuzzy sets reduces the fragility of the definitions. However, not all of the highlighted ambiguities can be addressed using fuzzy sets since this approach requires the term or phrase to be measurable (Zhang, Ju, & Liu, 2017). The ambiguity of terms like old, fast, quiet, and suchlike can easily be addressed using fuzzy set theory. The rest should be linguistically specified. This is through better use of terminology and wording or even through extra explanations in appendix of contracts.

There are terms that are inherently fuzzy and can be addressed easily using a simple membership

function. One stage measurable is referred to such ambiguous terms: terms which are directly measurable and can be clarified using fuzzy sets in one stage.

*"The new engine must be quieter than the current ones"*: The noise level is measurable and hence the difference in the noise level of the new one compared with the current one can be expressed using fuzzy set theory;

*"The product should be delivered in less than a month"*: The delivery time is measurable so that delay can be defined using fuzzy set theory;

*"The machine should not be noisy"*. Similar to the first sentence, as the *machine* noise is measurable, the expected level of noise can be clarified using fuzzy set theory;

To make it clearer, assume that a contract requires product B to be quieter that product A. If the noise level of product A is $\alpha$ db, and the ideal noise level for the buyer is $\beta$ db, the membership function can be defined as follows (Noise level of product B: NL_B).

$$\mu_{NL_B} = \begin{cases} 0 & \alpha \leq NL_B \\ \dfrac{\alpha - NL_B}{\alpha - \beta} & \beta < NL_B \leq \alpha \\ 1 & NL_B < \beta \end{cases}$$

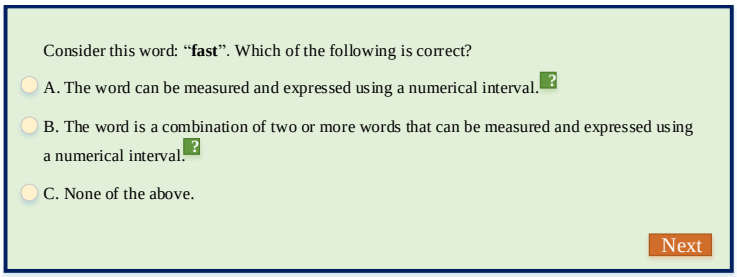
The above example shows how fuzzy logic, a soft computing technique, can be integrated with crowdsourcing and NLP. This integrated approach enables the building of a framework that is explained in the next section.

**HIT Formation**

In this section, fuzzy terms are identified, and a data pool of fuzzy terms is built by crowdsourcing. Using crowdsourcing instead of experts saves time and cost. Then, the terms are highlighted and presented to the user for clarification using fuzzy graphs. Since our assumption is that the user is not familiar with fuzzy logic, we ask the user just two simple questions and then the calculations are done through an algorithm which is presented by pseudocode.

**Building a Data Pool of Fuzzy Terms Using Crowdsourcing**

As mentioned previously, not all the terms that are highlighted using NLP can be addressed through fuzzy logic. Therefore, to connect fuzzy logic to NLP we first need to identify which words are fuzzy. To do this we use a simple rule in designing the Human Intelligence Task (HIT) (Whitla, 2009). A word is considered potential for clarification using fuzzy logic if it is not specified; however, it can be expressed by an interval of numbers or measurable concept(s). The word can have such specification itself, namely one-stage fuzzy, or can be expressed as a combination of words with such specification, namely two-stage fuzzy. To recognize this, with each word the following question (HIT) is sent to the crowd:




Some might find exceptions to this rule, but since the rule is relatively comprehensive and very easy to understand for a none-expert, we would still prefer to use the rule for the crowdsourcing. With respect to the option that the crowd uses, the word is classified. These words for which option A is selected are added to a one-stage fuzzy pool. In contrast, those words for which option B is selected are added to a two-stage fuzzy pool. Note that a word might be recognized fuzzy by crowd but, based on the sentence in which it has been used, the user recognizes it as non-fuzzy. Figure 4 shows the processes of building and using the databases.

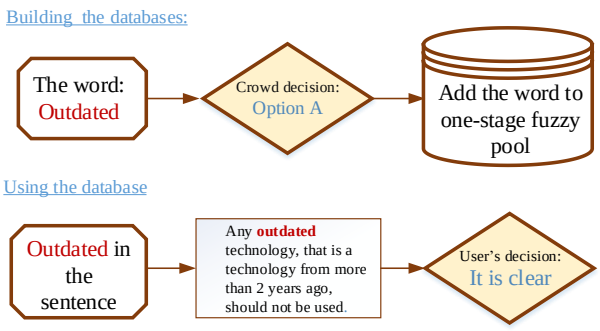



**Figure 2: Building and using databases**

## 1. Framework

The framework begins with a contract as the input and the following steps are applied.

Steps:

1. NLP scans the contract and highlights ambiguities. Assume n phrases are highlighted.
2. Experts check ambiguities which lack a high level of certainty and they are approved or rejected. Those which are rejected (k) are unhighlighted. While monitoring the phrases identified by NLP, the expert might notice and highlight 'h' unrecognized ambiguities and highlight them. Actions of the experts are reported back to the system to improve the framework.
3. A list of 'm=(n-k)+h' ambiguities is reported to fuzzy experts.
4. Fuzzy experts clarify these which can be addressed using fuzzy logic.
5. Contracting experts clarify the remaining 'm-p' phrases in the contract using more specific linguistic terms.
6. All of the m phrases are reported to the contracting experts to consider and modify regarding any legal issues. Then the contract is ready to sign.
7. Errors of the delivered product are investigated and, if relevant to the text of the contract, are reported to the framework.

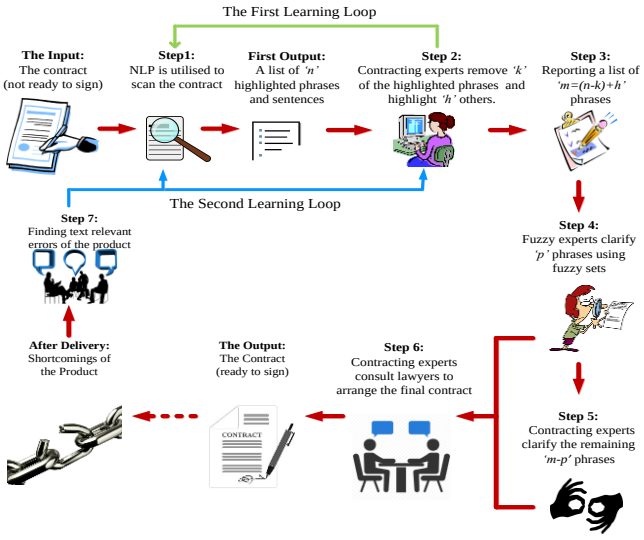



**Figure 3: The framework**

Note: Based on the above framework, the role of fuzzy set theory in clarification of a contract is computed as follows.

$$R_{FZ} = \frac{p}{(n-k)+h}$$

Using templates unifies the entire contract. To do so will help machines to understand what is written in the contract and, of course, find ambiguities. After the ambiguities are highlighted, fuzzy sets are used to address those phrases which are measurable like speed, power, consumption and similar.

**Algorithm (contract)**

**Input:** pool of fuzzy ambiguous terms: **ω**, a given contract: **contract**
**Output:** Updated set of fuzzy ambiguous terms: **ω**

```
A ← tokenizer(contract)
A ← normalizer(A)
B ← Sentences(A)
for i=1: |A|
   if (A_i ∈ ω) then
      φ_i ← A_i
   endif
end
t ← 0
T ← A − φ
for i=1: |T|
      t ← t + 1
      k ← Index(T_i, B)
      HIT_t ← HIT.Formation(T_i, B_k)
end
```

```
workers ← post(HIT)
[quality, labels] ← EM(workers)
x ← 0
for j=1:t
  if (labels_j = 1) then
    x← x + 1
    Y_x ← HIT_j
  endif
end
Fuzzy(Y_x ∪ φ)
ω ← Y_x ∪ ω
Return ω
```

Accuracy of the human adjustment is obtained by using well known quality control mechanisms in crowdsourcing such as an Expectation Maximization (EM) algorithm (Zhang, Chen, Zhou, & Jordan, 2016) and are recorded in case of any errors occurring after signing the contract. The recorded performance of experts is refined for use in the post-adjustment role when the contract ends. After NLP highlights the ambiguities and the experts approve highlighting, a list of ambiguities is delivered to fuzzy experts to apply fuzzy set theory.

## 2. Conclusion

A level of ambiguity is commonly involved in buyer-supplier relationships. Consequently, misunderstandings about the requirements and the receiving of unsatisfactory products becomes very likely. To date, insufficient studies have been undertaken that investigate this problem. Here, the application of intelligent techniques is suggested to address the issue. This study proposes an integrated framework using the fuzzy logic, crowdsourcing and NLP. The integrated method is capable of working semi-automatically in recognizing and resolving ambiguities. This research contributes to contract theory through leveraging the mentioned techniques in automated or semi-automated contract monitoring.

### References


Asadabadi, M. R., Saberi, M., & Chang, E. (2017). *A fuzzy game based framework to address ambiguities in performance based contracting.* Paper presented at the Proceedings of the International Conference on Web Intelligence.

Azemati, H., Belinsky, M., Gillette, R., Liebman, J., Sellman, A., & Wyse, A. (2013). Social impact bonds: lessons learned so far. *Community Development Investment Review*(01), 023-033.

Dick, J., Hull, E., & Jackson, K. (2017). *Requirements engineering*: Springer.

Duren, J. V., Dorée, A., & Voordijk, H. (2015). Perceptions of success in performance-based procurement: Differences between clients and contractors. *Construction innovation, 15*(1), 107-128.

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of management review, 14*(1), 57-74.

Falessi, D., Cantone, G., & Canfora, G. (2013). Empirical principles and an industrial case study in retrieving equivalent requirements via natural language processing techniques. *IEEE Transactions on Software Engineering, 39*(1), 18-44.

Femmer, H., Fernández, D. M., Juergens, E., Klose, M., Zimmer, I., & Zimmer, J. (2014). *Rapid requirements checks with requirements smells: two case studies.* Paper presented at the Proceedings of the 1st International Workshop on Rapid Continuous Software Engineering.

Femmer, H., Fernández, D. M., Wagner, S., & Eder, S. (2017). Rapid quality assurance with requirements smells. *Journal of Systems and Software, 123*, 190-213.

Glas, A. H., Henne, F. U., & Essig, M. (2018). Missing performance management and measurement aspects in performance-based contracting: A systematic process-based literature analysis of an astonishing research gap. *International Journal of Operations & Production Management*.

Gleich, B., Creighton, O., & Kof, L. (2010). Ambiguity detection: Towards a tool explaining ambiguity sources. *Requirements Engineering: Foundation for Software Quality*, 218-232.

Griffith, D. A., & Zhao, Y. (2015). Contract specificity, contract violation, and relationship performance in international buyer–supplier relationships. *Journal of International Marketing, 23*(3), 22-40.

Gruneberg, S., Hughes, W., & Ancell, D. (2007). Risk under performance-based contracting in the UK construction sector. *Construction Management and Economics, 25*(7), 691-699.

Hooper, L. (2008). Paying for performance: Uncertainty, asymmetric information and the payment model. *Research in Transportation Economics, 22*(1), 157-163.

Hossain, M., & Kauranen, I. (2015). Crowdsourcing: a comprehensive literature review. *Strategic Outsourcing: An International Journal, 8*(1), 2-22.

Juergens, E., Deissenboeck, F., Feilkas, M., Hummel, B., Schaetz, B., Wagner, S., . . . Streit, J. (2010). *Can clone detection support quality assessments of requirements specifications?* Paper presented at the Software Engineering, 2010 ACM/IEEE 32nd International Conference on.

Kof, L. (2007). *Treatment of passive voice and conjunctions in use case documents.* Paper presented at the International Conference on Application of Natural Language to Information Systems.

Koning, P., & Heinrich, C. J. (2013). Cream-skimming, parking and other intended and unintended effects of high-powered, performance-based contracts. *Journal of Policy Analysis and Management, 32*(3), 461-483.

LÊgreid, P. (2017). *Transcending new public management: the transformation of public sector reforms*: Routledge.

Lu, J. (2014). The Performance of Performance-based Contracting in Human Services.

Lu, J. (2016). The Performance of Performance-Based Contracting in Human Services: A Quasi-Experiment. *Journal of Public Administration Research and Theory, 26*(2), 277-293.

Manes, E., & Tchetchik, A. (2018). The role of electronic word of mouth in reducing information asymmetry: An empirical investigation of online hotel booking. *Journal of Business Research, 85*, 185-196.

Martin, L. L. (2015). Performance-Based Contracting. *Government Contracting: A Public Solutions Handbook*, 61.

McCarthy, I. P., Silvestre, B. S., & Kietzmann, J. H. (2013). Understanding outsourcing contexts through information asymmetry and capability fit. *Production planning & control, 24*(4-5), 277-283.

Michelucci, P., & Dickinson, J. L. (2016). The power of crowds. *Science, 351*(6268), 32-33.

Mouzas, S. (2016). Performance based contracting in long-term supply relationships. *Industrial Marketing Management*.

Omizzolo Lazzarotto, B., Borchardt, M., Pereira, G., & Almeida, C. (2014). Analysis of management practices in performance-based outsourcing contracts. *Business Process Management Journal, 20*(2), 178-194.

Pozzetti, A., & Clark, C. B. G. (2015). Fuzzy logic application in performance-based contracting process. *Journal of Aerospace Operations, 3*(2), 57-89.

Rosadini, B., Ferrari, A., Gori, G., Fantechi, A., Gnesi, S., Trotta, I., & Bacherini, S. (2017). *Using NLP to Detect Requirements Defects: An Industrial Experience in the Railway Domain.* Paper presented at the International Working Conference on Requirements Engineering: Foundation for Software Quality.

Rossanez, A., & Carvalho, A. M. (2016). *Semi-Automatic Checklist Quality Assessment of Natural Language Requirements for Space Applications.* Paper presented at the Dependable Computing (LADC), 2016 Seventh Latin-American Symposium on.

Schoenmaker, R., & de Bruijn, H. (2016). Embracing complexity in performance-based contracts for road maintenance. *International Journal of Productivity and Performance Management, 65*(1), 4-24.

Selviaridis, K., & Norrman, A. (2014). Performance-based contracting in service supply chains: a service provider risk perspective. *Supply Chain Management: An International Journal, 19*(2), 153-172.

Selviaridis, K., & Wynstra, F. (2015). Performance-based contracting: a literature review and future research directions. *International Journal of Production Research, 53*(12), 3505-3540.

Sharma, S., & Pandey, S. (2018). Revisiting Requirement Analysis Techniques and Challenges. In *Soft Computing: Theories and Applications* (pp. 667-678): Springer.

Ssengooba, F., McPake, B., & Palmer, N. (2012). Why performance-based contracting failed in Uganda–an "open-box" evaluation of a complex health system intervention. *Social science & medicine, 75*(2), 377-383.

Sultana, M., Rahman, A., & Chowdhury, S. (2013). A review of performance based maintenance of road infrastructure by contracting. *International Journal of Productivity and Performance Management*, *62*(3), 276-292.
Sumo, R., Valk, W., Weele, A., & Duysters, G. (2016). How Incomplete Contracts Foster Innovation in Inter-Organizational Relationships. *European Management Review*.
Sumo, R., van der Valk, W., van Weele, A. J., & Bode, C. (2014). *Fostering incremental and radical innovation through performance-based contracting in inter-organizational relationships.* Paper presented at the The 23rd International IPSERA Conference, Johannesburg, South-Africa.
Visnjic, I., Jovanovic, M., Neely, A., & Engwall, M. (2017). What brings the value to outcome-based contract providers? Value drivers in outcome business models. *International Journal of production economics*, *192*, 169-181.
Voordijk, H. (2015). Perceptions of success in performance-based procurement. *Construction innovation*, *15*(1), 107-128.
Wang, S., Qing, L. J., Wang, H., & Li, H. Y. (2018). Integrated assessment of environmental performance-based contracting for sulfur dioxide emission control in Chinese coal power plants. *Journal of Cleaner Production*.
Whitla, P. (2009). Crowdsourcing and its application in marketing activities. *Contemporary Management Research*, *5*(1).
Zhang, W., Ju, Y., & Liu, X. (2017). Multiple criteria decision analysis based on Shapley fuzzy measures and interval-valued hesitant fuzzy linguistic numbers. *Computers & Industrial Engineering*.
Zhang, Y., Chen, X., Zhou, D., & Jordan, M. I. (2016). Spectral methods meet EM: A provably optimal algorithm for crowdsourcing. *Journal of Machine Learning Research*, *17*(102), 1-44.