Evaluation of the Linked Open Data Quality Based on a Fuzzy Logic Model

Esteban Arias Caracas, Daniel Fernando Mendoza López, Paulo Alonso Gaona-García, Jhon Francined Herrera Cubides, Carlos Enrique Montenegro-Marín

Evaluation of the Linked Open Data Quality Based on a Fuzzy Logic Model

Esteban Arias Caracas[1][0000-0002- 2119-8103] Daniel Fernando Mendoza López[2][0000-0001-6289-1257], Paulo Alonso Gaona-García[3][0000-0002-8758-1412], Jhon Francined Herrera Cubides[4] [0000-0002-3608-715], Carlos Enrique Montenegro Marín[5] [0000-0002-3608-715]

Faculty of Engineering, Universidad Distrital Francisco José de Caldas, Bogotá, Colombia

1 eariasc@correo.udistrital.edu.co
2 dfmendozal@correo.udistrital.edu.co
3 pagaonag@udistrital.edu.co
4 jfherrerac@udistrital.edu.co
5 cmontenegrom@udistrital.edu.co

Abstract. Linked Open Data has been one of the most widely used online data publishing methods in recent years. This growth means that the quality of this data is required for the benefit of consumers and people who wish to use this data. There are approaches based on classical mathematical models, however, most of these results are too linear; that is, they use conventional evaluators to define both quality aspects and results. In response, a new approach based on fuzzy logic is constructed as an application, which aims to complement and compare traditional models without the need to restrict the quality aspects with which it can be measured. As a methodology, it is done by obtaining data from each dataset through the SPARQL Endpoints provided by high category datasets, classifying them within accessibility and trust dimensions, represented in 4 values: response time, scalability, trustworthiness and timeliness. This analysis is done internally for the values within the accessibility dimension, and externally for the values within the confidence dimension. In this way, it is possible to know or determine a better general quality approximation of the Linked Open Data according to a large number of quality evaluation variables, or even parameterize its own aspects in the model as a complement to the already established models, through the concept of fuzzy logic.

Keywords: Linked open data, Fuzzy logic, Quality measurement

1 Introduction

Linked Open Data has been one of the most recent changes in information in recent years, specifically the way in which data is published, distributed and consumed [1]. These data can easily be uploaded and updated by any type of organization, be it individuals, small groups of people, educational organizations, social networking sites and even government agencies [2]. Due to this large number of people, which can upload data to the Web, this model has grown exponentially, from 12 datasets in 2007, to approximately 300 in September 2011, and 9,960 datasets in 2016 [3], taking into account that this number is accumulated from the data catalogs: data.gov, publicdata.eu and datahub.io [4]; three of the main collections of datasets available to the public.

This growth in Linked Open Data requires methods or tools that can handle this data, to make it "secure, stable, fast and accurate; in other words, have a better quality," [5]. However, quality is a very complex concept; defining what is good quality or not is very subjective and cannot be defined in one way or by a simple judgment [2, 6].

For this reason, many researchers have been looking for methods to complement the quality of the data and administer them for later evaluation. Some of these researchers have created software that can evaluate quality with mathematical procedures, such the quality measurement software, "Luzzu" [6]. However, much of these results are extracted from classical or conventional mathematical models. This causes the calculated quality to possess a certain degree of uncertainty. Therefore, a formulated problem is generated: How to calculate the quality of Linked Open Data in a more precise way, with a considerable amount of quality variables to take into account?

As a new solution to the previous problem, modeling based on fuzzy logic is a solution that can provide the measurement of quality, taking into account the tolerance of intermediate values between conventional evaluators [7]. To cover the complexity of quality, it has approached the classification of quality through dimensions [8]. The proposed model covers 2 dimensions, of which four aspects will be represented in order to evaluate the quality of the linked open data, which will help to show the capacity of the fuzzy logic model when supporting a large number of quality aspects, and obtain a more accurate approximation of quality.

2 Theoretical Background and Related Work

2.1 Quality Dimensions

Datasets can be analyzed and classified through different dimensions, which can be contextual, trustworthy, intrinsic, among others [8]. These dimensions are classifications of groups of different variables or data quality measurement values or variables. For this model, the trust and accessibility dimensions were the most appropriate approaches to analyze the model.

The reason why these dimensions were chosen resides in the importance of each dimension can generate and the relationship between factors linked to the opinion of the client and linked to the functionality of the data set. The combination of both factors can arrive at a closer approximation to correctly measure the quality of the data, as well as to build the model as comprehensible to the user as possible.

But each dimension has different values or variables to work with. As an example, intrinsic dimensions classify variables such as accuracy, consistency or conciseness [8]. These dimensions can be defined differently for each author, however, they share similar approaches and characteristics. For this model, it is defined by the values of Response Time, Scalability, Trustworthiness and Timeliness.

The classification of each concept to its respective dimension results in the grouping of the response time and scalability in the dimensions of accessibility and the Trustworthiness and Timeliness in the confidence dimension.

2.2 Fuzzy Logic

The need to specify the fuzzy logic as the model to work was justified by the importance of changing the paradigm of mathematical results during studies during the last years. In classical mathematical concepts, variables can only be represented in 0 or 1, true or false, among others. In the measurement of quality, this type of results is ambiguous, since quality cannot exist or not exist. It is a value that can be partially good or partially bad, partially true or partially false [9]. Quality, for example, is something that cannot be described in a classic model of good or bad so easily; leads to ambiguous results and inaccurate results, but Fuzzy Logic, considering that it uses rules that define quality in segments and results that can be represented in more than two ways or variables, can adequately define a better approximation of the Data Quality evaluation.

2.3 Related Work

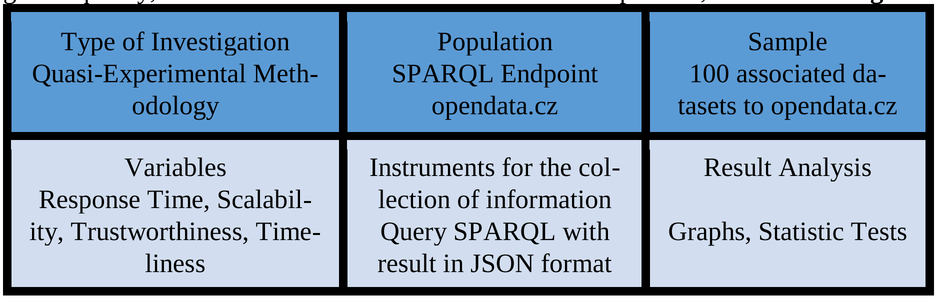
It is worth noting that both the fuzzy logic, which is the model used, and the open data are quite recent concepts and both have a very strong affinity, as well as a greater use during the last years [10]. Due to this reason, there are very few previous works similar to the one in this article.

The union of these two concepts arises from their compatibility and innovation. The representation of the rules that define the quality in segments of more than two answers can adequately define a better approximation of the evaluation of Data Quality, without the need of great requirements both for its main design and its portability, thus allowing to add more quality variables and more dimensions to work, for later calculation of quality more accurately.

The most outstanding work to take into account is the one by Daniel Lewis and Trevor Martin about the use of fuzzy logic for the analysis of ontologies and vocabularies within of Linked Open Data [11]. Mainly the fuzzy logic model to use in this article is the traditional one, while they demonstrated their investigation with the approximation X-μ, and the fact that the focus is on ontologies of linked open data, when this model seeks to create a new approach to a quality measurement of linked open data. Similarly, there are previously developed frameworks that seek to solve the aforementioned problems, the most similar to the case of this article is the "Luzzu" software. Its main objective is "to be scalable, extensible, interoperable and customizable" [6]. This framework works through the selection of quality metrics to be used within a default dataset or a SPARQL Endpoint. The Luzzu framework uses many more aspects of quality, with a capacity of 22 aspects of quality or metrics, related through nine dimensions of quality [6].

3 The Proposed Methodology

As a modeling of the methodology, it was decided to use a quasi-experimental empirical study, which allows estimating the impact of the different aspects of quality to obtain a global quality, without the use of random variables in the process, as shown in **Fig. *1***.



Type of Investigation Quasi-Experimental Methodology	Population SPARQL Endpoint opendata.cz	Sample 100 associated datasets to opendata.cz
Variables Response Time, Scalability, Trustworthiness, Timeliness	Instruments for the collection of information Query SPARQL with result in JSON format	Result Analysis Graphs, Statistic Tests

Fig. 1. Methodological design graphic, source: own elaboration

As a population the dataset of opendata.cz is taken into account, which has its own RDF Query Language (SPARQL) Endpoint, by which query type queries are carried out. As a sample, 100 datasets were taken associated with the main dataset opendata.cz, located in the Czech Republic. The SPARQL Endpoint corresponding to the opendata.cz dataset was used as instruments for data collection, and a JSON file for its subsequent analysis within the model was obtained as a result of a query to this endpoint. As a model analysis plan, it has been decided to compare quality values between the two cases raised for the visualization of the effect of more or less variables included within the fuzzy logic model. In turn, it was decided to show the comparative graphs between both cases for the values resulting from the evaluated quality, at the same time to visualize by means of tables statistical tests such as the deviation and the standard error.

The modeling for the evaluation of data quality in Linked Open Data can be built with a fuzzy logic approach, defining whether the quality is low, medium or high. Due to the represented model that uses a centroid method, since the need to improve previous models of data quality with a considerable number of inputs or quality criteria, allows us to obtain a percentage approximation value. As a percentage that is represented between a range and this truth value is more extended than the classical mathematical values of 0 and 1, the established ranges represent values of real life, such as low, medium or high (Fig. 2).

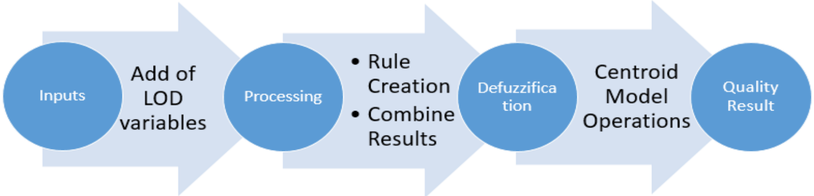


Fig. 2. Structure graph of fuzzy logic, Source: Own elaboration

The fuzzy logic model requires the evaluation of each of the four quality measurement channels, also known as the background of the model, through a series of rules, to then evaluate the output to determine if the quality of the data is high, medium or low. Two cases are evaluated: for the first case all four aspects are taken and the quality is measured with them. In the second case, 2 of the aspects are taken and redefined in their worst possible values and evaluate the quality of the data in a similar way to the first case. The main objective of these cases is to evaluate and compare the results considering that one case has many more factors than the other, and therefore is more accurate [8].

The first entry to evaluate is the Response Time, in which it can be calculated using the capacity in which the analyzed dataset is available and can respond to requests, because it is defined as “a data set can work well only if It is available and has a low response time” [12]. As a model definition within a range between 0 and 1, the response time is 1 if a response is received when requesting internal data from each dataset and the value is 0 otherwise. (Fig. 3).

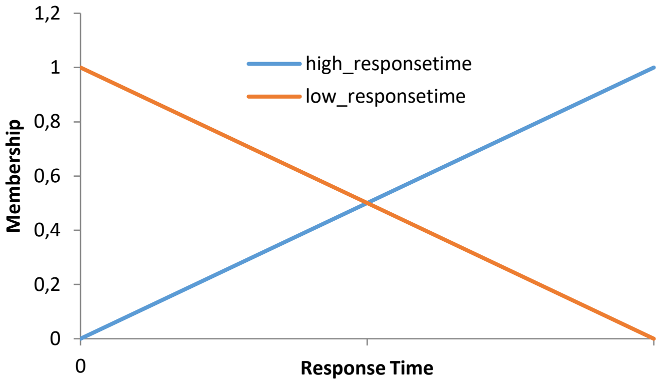


Fig. 3. Fuzzy logic model for the first case, response time. Source: Own elaboration

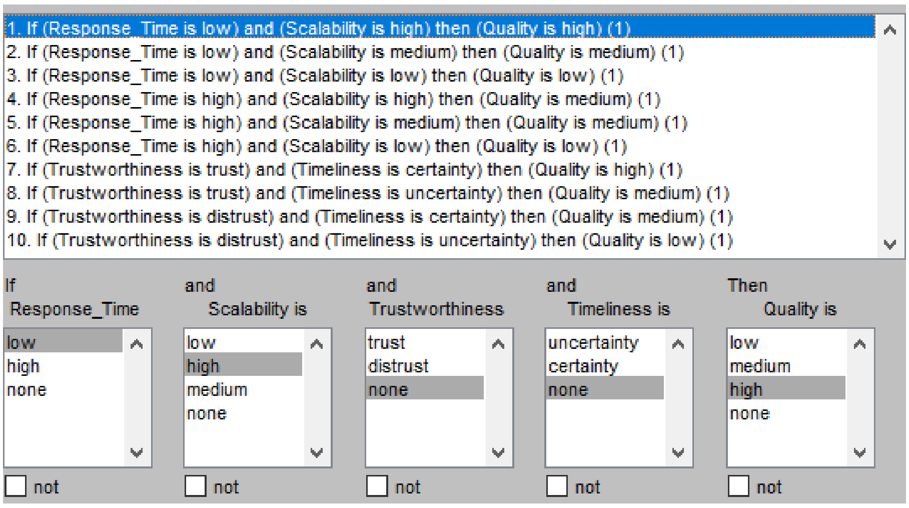
The second input to be measured in the model is scalability. Scalability measures the ability to respond to multiple users or requests at the same time [8]. The evaluation of this concept is taken by the concept of concurrency that supports the service that exposes the endpoint. As a methodology, it is measured by one and four users towards each of the datasets, performing a simulation in which each of these users makes a query towards the endpoint at the same time. After this, the average server response time is calculated for each user case and then applied a division between each average time of one and four users. This response variable will be expressed within a range [0,1], in which the value 0 is considered the lowest possible scalability and 1, the highest.

The relationship between the average time and the generation of the formula was based on the formula of the Timeliness assessment model of Olaf Hartig [13]. In his work, due to the similarity and the evaluation method used, which allowed to verify mathematically in a range, adaptable to this model of fuzzy logic.

The third entry to analyze in the model is Trustworthiness. The reliability allows to evaluate if the information and the data are classified as true and correct within the needs of each user of them. The Trustworthiness is measured in an interval [-1,1] that considers -1 as absolute distrust and 1 as absolute confidence.

The fourth entry of the model is Timeliness. This concept defines the moment in which the datasets were updated or modified for the last time. As a measurement, Timeliness is defined in an interval [0,1] in which 0 represents uncertainty and the result 1 represents certainty.

Each case of the fuzzy logic model has three specific rules, one defining each possible case of quality within each dimension. It is necessary to clarify that, the output value called Quality within each rule for each dataset is according to the dimension in which the rule is classified, but not to the global quality. This is for the purpose of measuring global quality taking into account all the proposed rules and not only one or two that are met, at the same time to associate each aspect with its related ones and not to mix them, since comparing non-related metrics does not have a lot of logic. According to figure 3 and thanks to the software MATLAB and the tool Fuzzy Logic Toolbox, the rules for the Accessibility Dimension (from number 1 to number 6) and the rules for the Trust Dimension (from number 7 to number 10) are:



1. If (Response_Time is low) and (Scalability is high) then (Quality is high) (1)
2. If (Response_Time is low) and (Scalability is medium) then (Quality is medium) (1)
3. If (Response_Time is low) and (Scalability is low) then (Quality is low) (1)
4. If (Response_Time is high) and (Scalability is high) then (Quality is medium) (1)
5. If (Response_Time is high) and (Scalability is medium) then (Quality is medium) (1)
6. If (Response_Time is high) and (Scalability is low) then (Quality is low) (1)
7. If (Trustworthiness is trust) and (Timeliness is certainty) then (Quality is high) (1)
8. If (Trustworthiness is trust) and (Timeliness is uncertainty) then (Quality is medium) (1)
9. If (Trustworthiness is distrust) and (Timeliness is certainty) then (Quality is medium) (1)
10. If (Trustworthiness is distrust) and (Timeliness is uncertainty) then (Quality is low) (1)

Fig. 4. Fuzzy logic model for the first case, response time. Source: Own elaboration

It is necessary to emphasize that the relationship that has the response time and the scalability shown in Fig. 4, is mainly the performance that both variables specify when evaluating the dataset. Scalability successively measures the response time of each dataset, so the result of the response time will directly affect the scalability result. The relationship that maintains Trustworthiness and Timeliness sown in Fig. 4, is mainly from the internal analysis of each dataset. Both Trustworthiness and Timeliness take internal data from the dataset as date of creation, authors, dataset of origin, among others, which internally define the confidence dimension for obtaining the quality of the data.

Regarding the output result, the model will take into account the generated rules and produce an interval percentage between 0% and 100%, 0% representing the worst possible quality and 100% representing the best possible quality.

4 The Infrastructure of the Implemented Model

The capture of the data (or the population to be taken into account in the research) was done through the SPARQL Endpoint of the data set "opendata.cz", known for its interest in "building an open data infrastructure that allows access to public data in the Czech Republic" [14]. Within this Endpoint, the number of data sets that the SPARQL query displays is 100, taking it as the investigative sample of the process. It is necessary to emphasize that the approach used requires both the internal data of the SPARQL query and external data, taken mainly to measure the values of Response Time and Scalability within the framework.

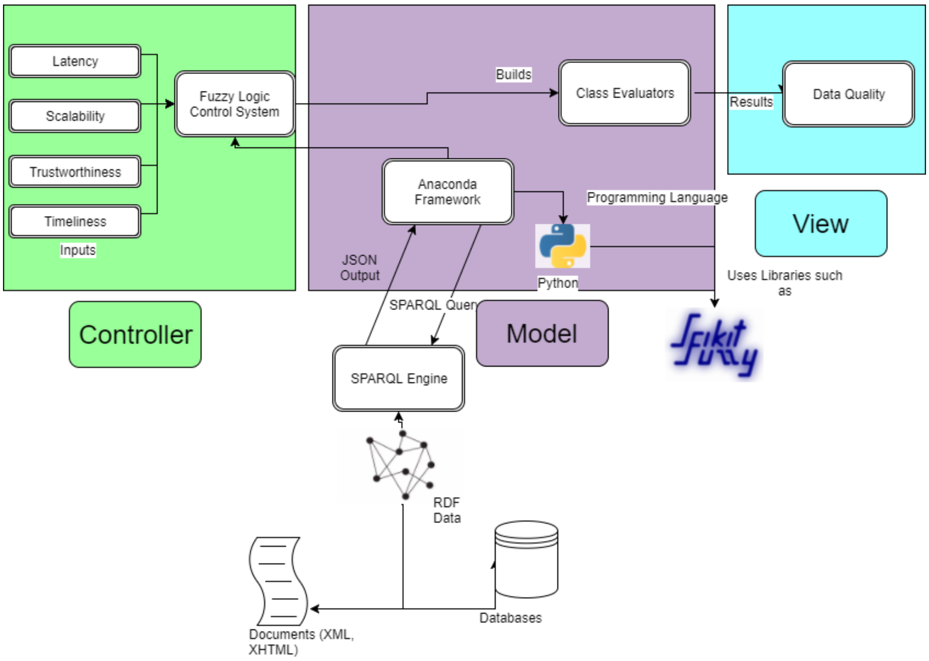


Fig. 5. Infrastructure of the Implemented Model. Source: Own elaboration

The SPARQL query used in the test model obtains the metadata results: the dataset title, the dataset description, the dataset creator (important for the Trustworthiness analysis), the dataset's contributors (important for the analysis of the Trustworthiness), the date of creation and modification of the dataset (important for the analysis of Timeliness), these grouped within a JSON file for later addition to the model. These are designed for the standards of the Semantic Web of RDF and the Vocabularies dcterms (Dublin Core Terms) and foaf (Friend Of A Friend).

The analysis of the data is done through Anaconda Framework, driven by the Python programming language, which allows to evaluate the data of a JavaScript Object Notation (JSON), which is a light interchangeable structured result of data generated by SPARQL Endpoints through the open server VIRTUOSO. As a note, the SPARQL query that obtains information shows the associated datasets, defining their relationship, point of origin and internal data such as the dataset author or the creation date of the dataset [4]. Mechanically, both the response time and the scalability are calculated by making requests based on HTTP / 1.1 of the SPARQL query, to obtain response times and calculate an average.

After obtaining the main data, the model proceeds to use controllers and evaluators defined for each antecedent as part of the structure in its programming, each with its specific function; the controllers allow the JSON data to be extracted and divided into segments, defined by the four dimensions of the quality of the data, and the evaluators execute the operations on the data to prepare them for processing in the model. Within the fuzzy logic model, the entries are updated and proceeds to compare the results with the 6 previously defined rules, and allow to obtain an output result per dataset.

5 Results

The data collection was successful for the 100 datasets to be analyzed, obtained in a JSON file as a result. To show results not extensive to the reader, only four sample datasets from the list of 100 datasets obtained from the SPARQL Endpoint of the dataset "opendata.cz" are shown in this section.

For the Response Time case, the average response time calculated as 43.73ms was compared to each time calculated. This procedure was executed approximately 50 times more and then the average of those times was obtained, in which it gave the result of 48.32 ms. It was possible to verify that each of the datasets analyzed within the study gave results within the JSON of the given request, that is, no null values or no response were obtained from the datasets, so the response time value for each of these datasets is 1.

Table 1. Examples of results of response times, Source: Own.

Dataset Name	Calculated Response Time
Czech municipalities	48.1128183467
Job applicants in regions of Czech Republic	47.8042141867
Institutional research plans	49.1565653333
R&D Programmes	47.9116424533

In the case of Scalability, the procedure to follow was a SPARQL request to extract internal data from each dataset, used within the cases of Trustworthiness and Timeliness. This process was executed an amount of 50 times more, obtaining as a result response times for one and four users separately, for a total added of 250 times. As a next step, each of the four user times were added, obtaining data from a single response time group, which were then compared with a user's data, using the average time of both groups. With this, the formula proposed above is applied and the average scalability result equals 0.900363599953. As a reference, this value is between a range of [0,1].

Table 2. Examples of scalability results. Source. Own elaboration

Dataset Name	**Calculated Scalability Result**
Czech municipalities	0.917890563599
Job applicants in regions of Czech Republic	0.891315467557
Institutional research plans	0.937077953964
R&D Programmes	0.921803070866

In the case of Trustworthiness, the natural way to measure this case is to take the author and collaborator values of each dataset and evaluate if these data are present (without null value). However, due to the empirical status of the study for the 100 sample datasets, the Trustworthiness was statically evaluated as 1, considering that all datasets contain authors and contributors verified by Datahub, a platform designed by the Open Knowledge Foundation.

In the case of Timeliness, the date of each dataset was taken into account as regards its creation and last modification. In order to specify and generalize the calculation of this factor, only the current year of this article (2017) was taken into account to compare both dates. As a result, you get a range between 0 and 1 per data set.

Taking into account the analysis plan previously proposed in the Methodology section, as a first step we studied the standard deviation and the error of the results of the model both for the quality cases and for the Response Time and Scalability due to the use of its average values to execute the model. The standard deviation of both quality cases is quite small, which can define the high precision of the calculated data, due to the low dispersion range between the mean and the values obtained [15]. It is worth noting that Case 2 has a larger Standard Deviation because taking only Timeliness and Response Time as factors that fluctuate the result, but all other variables are still present within the same values as Case 1, so a correlation between both cases exists and has similar standard deviation results, and, therefore, defining a high precision in the output results of the fuzzy logic model.

At the same time, the addition of the standard error confirms the fact that the sample of the data taken does not have a high discrepancy. Specifically, with the result of the quality in case 1, which contains all four quality variables, it is important to know that this discrepancy decreases, and thus allows recognizing that the model can support a greater number of quality variables without fluctuation much discrepancy found (Fig 6 and 7).

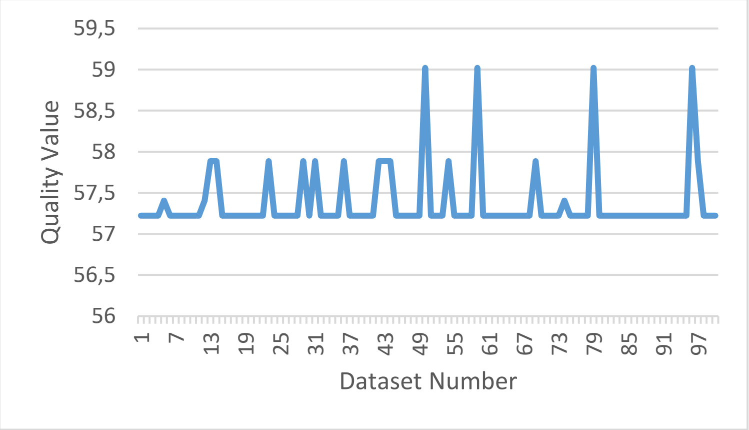


Fig. 6. Graph of the Quality of the Results, First Case. Source: Own.

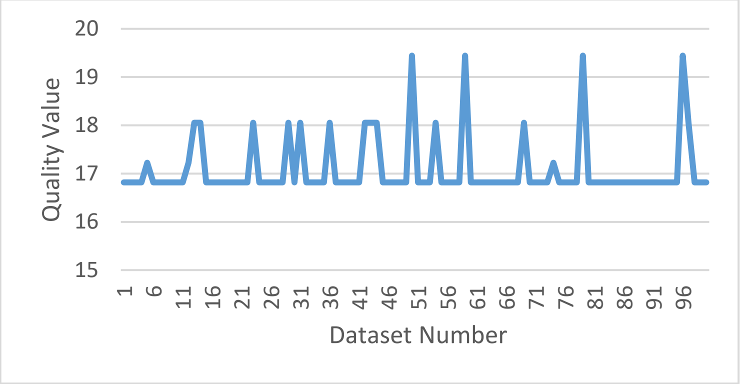


Fig. 7. Graph of the Quality of the Results, Second Case. Source: Own.

In relation to the results of the quality of the results for both cases, it is observed that the first case has a higher percentage than the second case due to having a better score in two of the dimension values, however, it is observed that both cases have peaks that mean higher quality. The main reason for this phenomenon is that Timeliness and Response Time fluctuate the results. In a real scenario, the peaks are represented by values that do not have a high Timeliness, proven by not having the best possible value in the interval, 1.

In the comparison of the Luzzu framework, although the modeling of both frameworks are different, it can be seen that their growth in terms of processing and speed based on the execution time of the models are linear. However, it is noted that the fuzzy logic model has a faster amount of time executed for the processing in comparison to Luzzu, making it have a better performance.

As an added value to this model, although it uses mathematical formulas similar to those of this model for the calculation of data [6, 12], Luzzu uses classic modeling to process data in a percentage way, without the advantages that fuzzy logic generates to obtain a more precise result, such as the establishment of rules according to dimensions.

6 Conclusion and Discussion

Linked Open Data has been growing exponentially in recent years, and will continue to grow more and more due to the full capacity for everyone to publish data on the web freely to share information. However, that only makes quality more and more important towards the future. An approach through fuzzy logic is a solution that has many advantages, such as the ability to mathematically define quality and focus on it deeply, rather than classical mathematical approaches. However, as an example, its full potential has not been proven; in this case, the same endpoint was evaluated, which means that quality aspects were similar, apart from facts such as the need to add more and more quality dimensions and, therefore, the use of more rules and operations. Another aspect that this model must consider is a greater inclusion of the user in the evaluation of quality; due to the need to evaluate the model personally and with the help of feedback, allowing the model to be even more precise. In turn, as seen in the comparison with other recent frameworks, there are limitations both of this fuzzy logic model, and of these frameworks, which can be mitigated or complemented. It is possible to find results that allow us to verify the main functionality of this concept, that is, in the definition of relative results, instead of absolutes, as in the case of "if it has quality or does not have quality "scenario.

In summary, the key contribution of the fuzzy logic model is the capacity of the quality calculation of Linked Open Data, related within the datasets, in a precise and controlled manner with a large number of variables and dimensions of quality to measure. As future work, we mainly seek to add a greater number of dimensions to achieve a global quality of the data, while adapting this model to other research techniques within the LOD field with different means and alternatives, according to the evolution of these data.

References

1. Hu, B., Rodrigues, E. M., & Viel, E. Capri. In Proceedings of the 16th International Conference on Information Integration and Web-based Applications & Services - iiWAS 2014 pp. 217–223. ACM Press. New York, USA (2014) https://doi.org/10.1145/2684200.2684336
2. Bonatti, P. A., Hogan, A., Polleres, A., & Sauro, L. Robust and Scalable Linked Data Reasoning Incorporating Provenance and Trust Annotations. Web Semantics: Science, Services and Agents on the World Wide Web, 9(2), pp. 165–201 (2011). Retrieved from http://aidanhogan.com/docs/saor_ann_final.pdf
3. Auer, S., Ermilov, I., Lehmann, J., & Martin, M. LODStats - 9960 datasets. Retrieved August 14, 2017, (2016) from http://stats.lod2.eu/

4. Ermilov, I., Lehmann, J., Martin, M., & Auer, S. LODStats: The Data Web Census Dataset. International Semantic Web Conference., pp. 38–46 (2016) Retrieved from http://jens-lehmann.org/files/2016/iswc_lodstats.pdf
5. Thakkar, H., Endris, K. M., Gimenez-Garcia, J. M., Debattista, J., Lange, C., & Auer, S. Are Linked Datasets fit for Open-domain Question Answering? A Quality Assessment. In Proceedings of the 6th International Conference on Web Intelligence, Mining and Semantics - WIMS 2016 pp. 1–12. ACM Press. New York, USA (2016). https://doi.org/10.1145/2912845.2912857
6. Debattista, J., Auer, Sö., & Lange, C. Luzzu—A Methodology and Framework for Linked Data Quality Assessment. Journal of Data and Information Quality, 8(1), pp. 1–32 (2016) https://doi.org/10.1145/2992786
7. Hellmann, M. Fuzzy Logic Introduction. Universite de Rennes, pp.1–9 (2001) Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.85.9757&rep=rep1&type=pdf
8. Zaveri, A., Rula, A., Maurino, A., Pietrobon, R., Lehmann, J., & Auer, S. Quality Assessment Methodologies for Linked Open Data A Systematic Literature Review and Conceptual Framework. Undefined, 1, pp. 1–5 (2012). Retrieved from http://www.semantic-web-journal.net/system/files/swj414.pdf.
9. Stella-vagaska Alena, H. Application of Fuzzy Principles in Evaluating Quality of Manufacturing Process. WSEAS TRANSACTIONS ON POWER SYSTEMS, 7(2), pp. 1–10 (2012) Retrieved from http://www.tuke.sk/fvtpo
10. Dernoncourt, F. Introduction to fuzzy logic. Massachusets Institute of Technology, pp. 1–21 (2013) Retrieved from http://aisii.azc.uam.mx/mcbc/Cursos/IntCompt/Lectura15.pdf
11. Lewis, D. J., & Martin, T. P. Managing Vagueness with Fuzzy in Hierarchical Big Data1. Procedia Computer Science, 53, pp. 19–28 (2015) https://doi.org/10.1016/j.procs.2015.07.275
12. Zaveri, A. Linked Data Quality Assessment and its Application to Societal Progress Measurement. University of Leipzig. (2015) Retrieved from https://core.ac.uk/download/pdf/35206278.pdf
13. Hartig, O., & Zhao, J. Using Web Data Provenance for Quality Assessment. Proceedings of the First International Conference on Semantic Web in Provenance Management, 526, pp. 29–34 (2009) Retrieved from http://ceur-ws.org/Vol-526/paper_1.pdf
14. Nečaský, M., Klímek, J., Chlapek, D., Kučera, J., Mynarz, J., & Svátek, V. OpenData.cz. (2015) Retrieved September 5, 2017 from https://opendata.cz/
15. DataStar, I. How to Interpret Standard Deviation and Standard Error in Survey Research. (2013) Retrieved September 7, 2017, from www.surveystar.com