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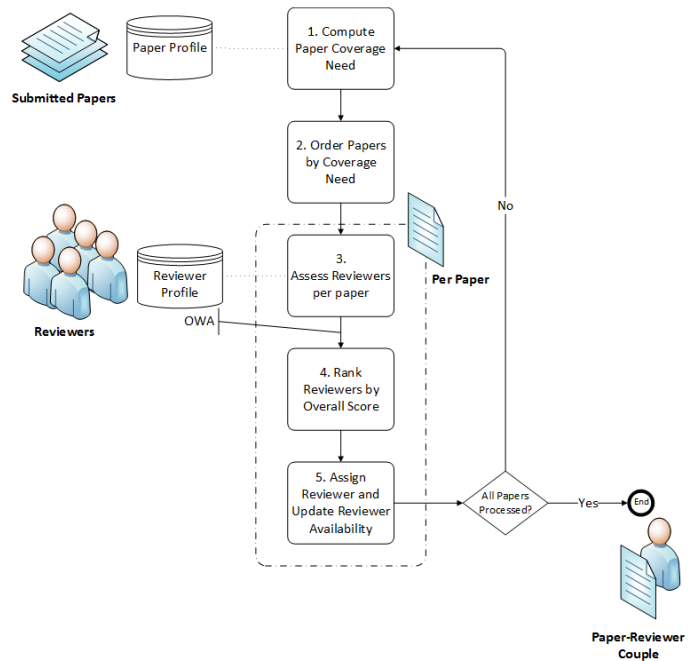

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A decision support tool using OWA for conference review assignment

Jennifer Nguyen, Sánchez-Hernández, Núria Agell, Xari Rovira, Cecilio Angulo

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- The method describes reviewer profiles beyond the traditional measure of expertise skills to include additional computed dimensions of recency, quality, and availability.

- Profile information are collected implicitly from multiple sources which are publicly available, reducing the time required from the conference chair, authors, and reviewers.

- An OWA (Ordered Weighted Average) aggregation function is applied to rank candidate reviewers, allowing the simultaneous use of relevant features without any filtering process.

A decision support tool using OWA for conference review assignment

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ABSTRACT

Assigning papers to reviewers is a large, long and difficult task for conference chairs and scientific committees. The paper reviewer assignment problem is a multi-agent problem which requires understanding reviewer expertise and paper topics for the matching process. This paper proposes to elaborate on some features used to compute reviewer expertise and aggregate multiple factors to find the fittest combination of reviewers for each paper. Expertise information is gathered implicitly from publicly available information and a reviewer profile is generated automatically. An OWA (Ordered Weighted Average) aggregation function is used to summarize information coming from different sources and rank candidate reviewers for each paper. General constraints for the RAP (Reviewer Assignment Problem) have been incorporated into a real case example: (i) conflicts of interest between a reviewer and authors should be avoided, (ii) each paper must have a minimum number of reviewers, and (iii) each reviewer load cannot exceed a certain number of papers.

1. Introduction

Assigning papers to reviewers is a non-trivial task for conference chairs and scientific committees. The task requires an optimal matching between reviewers and papers. To accurately accomplish this task, knowledge of reviewer expertise and paper topics are required. Often these assignments must be made within days after a submission deadline creating a huge burden on the conference chairs. This article goes in the direction of assisting conference chairs with matching a paper and reviewers.

A number of academic research and commercial software have tried to address the automation of the reviewer assignment problem (Charlin and Zemel (2013); Conry et al. (2009); Rigaux (2004)). Reviewer preferences or bids are used to represent reviewer research interests. However, some shortcomings can be associated with the bidding process. A reviewer may bid on papers for their novelty rather than their alignment with his/her research interests (Basu et al. (2001)). In addition, reviewers may search for papers using keywords and bid on papers returned in their search rather than considering all the papers in the conference (Charlin and Zemel (2013)).

Some systems determine reviewer expertise from their publications or webpages (Basu et al. (2001); Charlin and Zemel (2013); Pesenhofer et al. (2006)). This approach could help avoid the shortcomings from the bidding process. However, web sources could provide sparse information (Kalmukov (2013)). While expertise topics can be acquired from reviewers' publications, new PhDs and researchers, who are not so well published but knowledgeable in their field of research, may be missed as potentially good reviewers. Other systems obtain reviewer expertise by directly asking reviewers to select their areas of expertise from a predefined list of topics (Hartvigsen et al. (1999); Kalmukov (2011); Sun et al. (2008)). These systems would catch any new researchers' expertise but the process can be very time consuming for a busy reviewer.

In order to provide conference chairs with an overall view of a reviewer's expertise, we propose to build a profile for each reviewer consisting of seven features. Five of these dimensions are aggregated into a single quality score representing a reviewer's publishing accomplishments. The sixth variable corresponds to a second score representing a reviewer's areas of research and the third score, the seventh variable, *recency*, refers to papers published in recent years. To reduce the amount of time required from reviewers, we propose to create profiles from information extracted from public web pages. As this process can be completed at any time, conferences can develop and

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update profiles in advance of the conference paper assignment process.

As argued in Tayal et al. (2014), there exists imprecision associated with reviewer expertise levels. However, often in prior studies, reviewer expertise across different domains has been considered as a crisp set. As our information comes from multiple sources, an additional natural uncertainty exists. Therefore, we consider an Ordered Weighted Averaging (OWA) aggregation function (Yager (1996)) to summarize the information coming from different sources and rank the candidate reviewers for each paper.

The rest of the article is organized as follows. First, we provide a review of related work. Next, we explain the proposed methodology for defining paper and reviewer profiles, and matching papers to reviewers. In Section 4, we provide a simulated case example using data from some conferences. In Section 5, we evaluate our results from the real case example. Finally, we discuss our conclusions and future work.

2. Related Work

In this section, we review and compare related research on the reviewer assignment problem. Specifically, we characterize the existing literature according to four dimensions: Reviewer profile, Paper profile, Matching method, and Case implementation.

The first dimension, *Reviewer profile*, considers the elements which make up a reviewer profile and how they are determined. For example, a reviewer's area of expertise my be gathered by asking reviewers to select from a set of previously define keywords specific to the conference. The second dimension, *Paper profile*, considers elements that make up a paper's profile and how they are determined. For example, authors of each paper may be asked to enter or select from a set of keywords which best describes their paper. The third dimension, *Matching method* refers to the algorithmic approach used to assign reviewers to papers. Lastly, the fourth dimension, *Case implementation* refers to how the methodology was implemented. If the method was implemented in a real case scenario, the environment is also considered.

As it can be seen in Table 1, variables in both the reviewer and paper profiles were collected explicitly and/or implicitly. Information acquired explicitly requires input from the reviewer. Whereas, information acquired implicitly entails eliciting information in an automated way (Kalmukov (2011)). Most of the papers consider a set of predetermined keywords either for profiling reviewers or papers where a conference provides a set of keywords from which authors and reviewers select to represent their papers or expertise, respectively. However, the range of approaches considered for the matching method is very wide, varying from crisp to fuzzy methods. Regarding the types of applications, all of them are oriented towards either the conference reviewer assignment problem or assignment of experts to project proposals.

Our proposed method introduces two main advantages. First, it deals with information coming from several public sources to establish reviewer expertise and uses several variables to complete reviewer profiles. Second, an automated matching process, based on an aggregation function defined by an OWA operator, allows the simultaneous use of the relevant features without any filtering process.

3. Proposed Methodology

The first three out of four defined dimensions, that is, Reviewer profile, Paper profile, and Matching, are described for our proposed method. The actual Case implementation performed is left for the next section.

3.1. Defining the Reviewer Profile

We propose to represent a reviewer's profile using three measures related with his/her research topic interests, recency, and quality. The research topic interests vector represents a reviewer's area of expertise. The recency score refers to the papers published in recent years for the reviewer, while the quality score represents a reviewer's publishing accomplishments.

To gather information about each reviewer, we use global and local public sources. Global sources like Aminer[1] provide information on researchers from around the world in many different fields. In contrast, local sources like TDX[2] focus on a particular field of study and/or region of the world. Prior research in Basu et al. (2001) found that using more sources of information can lead to better performance.

Given a set of reviewers $\{Y_l\}_{l=1}^L$, all the possible research topics obtained from several websites for each reviewer are put into a common taxonomy using a dictionary of terms. The dictionary aligns common terms with the conference topics $\{T_k\}_{k=1}^m$. Automated alignment systems can be applied in this step, but it is vetted by an expert to ensure proper translation. Then, each research interest is translated to a conference topic. For each reviewer Y_l, the measure of his/her expertise in each conference topic is expressed as a vector $(y_{l1}, \ldots, y_{lm})$.

The recency score is defined as a weighted average impact factor of the papers published by a reviewer in the past N years as defined by Aminer[1].

Regarding the quality score, the features considered in our methodology are: the number of PhDs supervised, books and book chapters written, papers published (both journals and conferences), and their H-index. Note that since we use several sources of information, data consistency is not warranted, each source of information can provide different values for the features considered in the quality score. Therefore, the maximum value of each feature from the different sources is selected. Using an Ordered Weighted Averaging (OWA) function these values are aggregated into the score called quality.

Besides the previously considered variables, a reviewer's profile also contains a list of previous co-authors and the reviewer's availability. The list of co-authors enables the system

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[1] aminer.org
[2] tdx.cat

Table 1. Comparison of different approaches to the reviewer assignment problem

Paper	Reviewer Profile	Paper Profile	Matching Method	Case Implementation
Dumais and Nielsen (1992)	Abstracts provided by reviewers	Not applicable	Latent semantic Indexing	Conference Reviewer Assignment: Hypertext'91
Hartvigsen et al. (1999)	Predetermined keywords	Predetermined keywords	Capacitated transhipment problem	Conference Reviewer Assignment: Decision Sciences Institute annual meeting 1998
Merelo-Guervós and Castillo-Valdivieso (2004)	Predetermined keywords	Predetermined keywords	1) Greedy algorithm 2) Evolutionary algorithm	Conference Reviewer Assignment: Parallel Problem Solving from Nature 2002
Goldsmith and Sloan (2007)	1) Predet. keywords 2) Bids	Predetermined keywords	1) Min. cost flow problem 2) Stable marriage problem	Conference Reviewer Assignment: No experimental results
Sun et al. (2008)	Predetermined keywords	Predetermined keywords	1) Capacitated transportation problem 2) Heuristic	Assignment of experts to project proposals: Prototype - simulated data
Kalmukov (2011) and Kalmukov (2013)	Predetermined keywords	Predetermined keywords	Semantic similarity	Conference Reviewer Assignment: CompSysTech 2010 and 2011
Charlin and Zemel (2013)	1) Score from reviewer's papers 2) Bids	Not applicable	1) Latent Dirichlet Allocation 2) Supervised score prediction	Conference Reviewer Assignment: NIPS 2010, 2012, ICML, UAI, AISTATS, CVPR, ICCV, ECCV, ECML/PKDD, ACML, ICGVIP
Daş and Göçken (2014)	Predetermined keywords	Not applicable	1) Signed distance method 2) Ranking fuzzy numbers	Assignment of experts to project proposals: Toy example
Tayal et al. (2014)	Expert quality measurement from indicators	Predetermined keywords	Fuzzy equality operator	Assignment of experts to project proposals: prototype - simulated data
Sidiropoulos and Tsakonas (2015)	Keywords determined by authors	Keywords determined by technical program committee chair	Optimization method	Workshop Reviewer Assignment: SPAWC 2010

to avoid any conflicts of interest between the authors of conference papers and the proposed reviewer. The reviewer's availability is an indicator to be used in the matching procedure for assigning reviewers to papers.

3.2. Defining the Paper Profile

A paper profile consists of a paper's set of topic areas and a list of authors. The authors' names can be extracted from the paper submissions. To determine a paper's topic areas two steps are considered.

First, we determine a set of *concepts* from the entire set of paper submissions. The Latent Dirichlet Allocation (LDA) approach has been considered to generate this list. Originally introduced in Blei et al. (2003), it is an unsupervised topic modeling method. LDA has been used in other reviewer assignment systems such as the Toronto Paper Matching System (Charlin and Zemel (2013)). In our case, LDA considers the entire collection of n paper submissions $\{P_i\}_{i=1}^n$ and provides a set of con-

cepts, $\{C_j\}_{j=1}^s$. Each concept is defined by a group of words. In addition, LDA calculates the proportion of each concept C_j represented in each paper P_i, α_{ij}, and satisfies,

$$\sum_{j=1}^s \alpha_{ij} = 1. \tag{1}$$

Second, to translate these concepts into the set of conference topics $\{T_k\}_{k=1}^m$, each set of words representing a concept is combined with the conference theme and a topic in a search using Google Scholar[3]. Then, the frequency that each concept appears with each conference topic is normalized by the frequency of the conference topic and theme, and collected in a matrix $\mathbf{G} = (g_{jk}) \in [0, 1]^{s \times m}$, where each value of the matrix represents the frequency that the concept C_j appears with the

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[3] scholar.google.com

conference topic T_k in the search of all papers received for the conference. It is worth noting that each concept represents a combination of several conference topics,

$$C_j = \sum_{k=1}^{m} g_{jk} T_k. \tag{2}$$

Next, for each paper P_i, the vector of concept proportions provided by LDA, $(\alpha_{i1}, \ldots, \alpha_{ij}, \ldots, \alpha_{is})$, is multiplied by the column in the matrix $\mathbf{G}$ representing the topic T_k to obtain the relationship r_{ik} between the paper P_i and the topic T_k,

$$r_{ik} = \sum_{j=1}^{s} \alpha_{ij} \cdot g_{jk} \tag{3}$$

and avoid to use the 'intermediate' determined concepts. Hence, the matrix $\mathbf{R} = (r_{ik}) \in [0,1]^{nxm}$ is considered, whose rows correspond to the proportions of the conference topics covered in each paper P_i.

3.3. Assigning Reviewers to Papers

Assigning reviewers to papers refers to the matching procedure developed to identify a set of reviewers who satisfy the needs of the paper. In the associated methodology, four types of indicators are used to evaluate a match between possible reviewers and papers. The first type corresponds to the matching between topics covered in the paper and reviewers expertise. The other three indicators are quality, recency, and availability. The process flow to assign a set of reviewers to each paper is depicted in Fig. 1.

The proposed matching methodology consists of five steps which are detailed below: compute paper coverage need, order papers by coverage need, assess reviewers per paper, rank reviewers by overall score, and assign reviewer and update availability. Once all of the paper submissions have been received, the process may begin. Prior to its start, the following parameters should be set up: mp, the maximum number of papers to be assigned to a reviewer, nr, the number of reviewers needed to fully cover a topic in a paper, and each reviewer's availability set to 1. Steps 1-5 are applied in an iterative loop until the criterion "all papers are assigned to the required number of reviewers" is met.

Step 1. Compute paper coverage need. In each iteration, coverage need for all the papers is computed for each topic, considering topics already partially or fully covered by previously assigned reviewers. The calculus computes for each paper, according to the *nr* parameter, the extra reviewers needed for covering all topics related to the paper.

Step 2. Order papers by coverage need. The system ranks the papers by the coverage need value obtained in Step 1 in decreasing order.

Step 3. Assess reviewers per paper. Given the highest ranked paper P_i from Step 2, its candidate reviewers are identified based on the following steps:

1. Select reviewers with availability greater than 0. If the paper P_i already has reviewers assigned, filter those reviewers out.
2. Assess into partial scores each selected reviewer profile: reviewer research topic expertise according to the topics coverage need of the paper, along with three more scores, quality, recency, and availability of the reviewer.
3. Employ OWA to aggregate the p partial scores a_p into an *overall score*.

$$\phi_{owa}(a_1, \ldots, a_p) = \sum_{h=1}^{p} w_h \cdot a_{\sigma(h)} \tag{4}$$

being p = "number of topics not fully covered"+3 and $\sigma : \{1, \ldots, p\} \rightarrow \{1, \ldots, p\}$ a permutation such that $a_{\sigma(h)} \geq a_{\sigma(h+1)}, \forall h \in \{1, \ldots, p\}$, i.e., $a_{\sigma(h)}$ is the h-th highest value in the set $\{a_1, \ldots, a_p\}$.

Weights w_h are computed as the regular increasing monotone (RIM) function guided by the linguistic quantifier 'most of' expressed as,

$$w_h = Q\left(\frac{h}{p}\right) - Q\left(\frac{h-1}{p}\right), \ h \in \{1, \ldots, p\}, \tag{5}$$

where $Q(x) = x^{1/2}$.

Step 4. Rank reviewers by overall score. Rank in descending order reviewer scores obtained in Step 3 using an OWA of the partial scores.

Step 5. Assign reviewer and update availability. Reviewer Y_l, with the highest score, is assigned to paper P_i and his/her availability, initially set to 1, is reduced as defined by,

$$Av(Y_l)_{new} = Av(Y_l) - \frac{1}{mp}, \tag{6}$$

where $Av(Y_l)$ is the current availability of reviewer Y_l.

In the case of ties between two or more reviewers with the highest score, the "exclusiveness" of the topics known by each reviewer (in terms of the number of reviewers knowing the same topics) is used, in order to choose the reviewer with the least exclusive knowledge.

Once a reviewer is assigned, the system checks if all papers have met the reviewer assignment criterion. If the criterion has not been met, the system completes another iteration beginning at Step 1. If the criterion has been met, the system exits the loop.

4. A Simulated Case using Real Data

To validate the reviewer assignment quality we generated a simulated case using real data from three consecutive editions of an international small-sized conference.
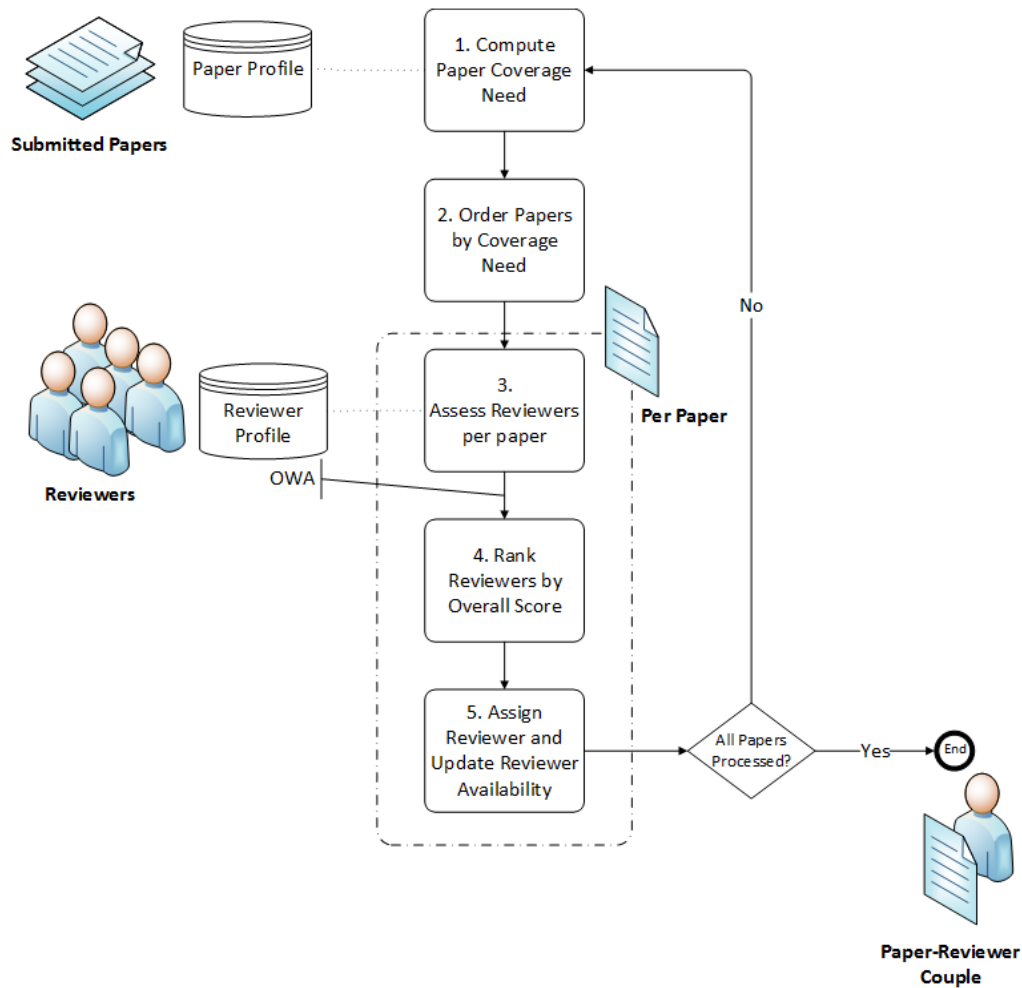
Fig. 1. Process flow of the proposed matching methodology for assigning reviewers to papers

4.1. Data Set

The data set consists of three consecutive conferences of the International Conference of the Catalan Association for Artificial Intelligence (CCIA 2014, 2015, and 2016). These conferences were combined into a simulated bigger one for two reasons. First, combining several conferences provided a larger number of paper submissions. Second, as these were the most recent conferences of CCIA, we were able to assume that the reviewer profile would be relatively similar for each year.

The papers and the reviewers from the three conferences were combined to form a single "conference". There were a total of 106 submitted papers and 96 Scientific Committee members. The Committee members' names are public on the conference web pages. We simulated the conference to take place in the current year. Therefore, the data collected to generate the reviewer profile is considered a representation of the current interests and activities of the reviewer.

To generate the reviewer profile we selected three global

sources: Aminer, ResearchGate[4], and dblp[5] and one local source: TDX (Catalan database of PhD theses). Each reviewer was identified according to his/her name, organizational affiliation, and network, when necessary. For each website, we gathered all the available information for each reviewer. When there were multiple entries for a reviewer from a single source, we took the one containing the most recent publications with the assumption that it implied a more current profile of the reviewer. If there were two records with articles published in the same year, we selected the one with the most profile information. We observed that the TDX website sometimes included the reviewer's own thesis in the collection of theses supervised and it was removed manually. All available information was translated to English. A dictionary of terms was created to translate terms representing reviewers' research interests from the different sources into the CCIA conference topics. Among the original 96 reviewers, only 51 had skills populated on their

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ResearchGate profiles. Therefore, as the main matching entities in a conference-reviewer environment are the expertise topics of the reviewers, we took into consideration only the subset of 51 reviewers for whom we could identify their skills.

The rest of the case follows the methodology described above and is implemented with the general constraints of a reviewer assignment problem. The number of reviewers per paper in this simulated case was set to 2, the maximum reviewer load (parameter mp) was initially set to 3 and the number of reviewers needed to fully cover a topic in a paper (parameter nr) was set to 2. However, the system automatically adjust to compensate for the ratio of reviewers per paper taking into consideration the parameter mp. Since 212 assignments are required (2 reviews per paper) from 51 reviewers, then the maximum number of papers assigned to a reviewer mp must be adjusted upward to 5.

5. Results and Evaluation

Many methods have been proposed to measure the performance of an automatic assignment system (Karimzadehgan et al. (2008); Mimno and McCallum (2007); Charlin and Zemel (2013)). However, there is no standard method to our knowledge. We applied three different techniques to evaluate the performance of our method from the perspectives of the reviewers, papers, and an expert's opinion.

5.1. The Overall Perspective

First, we assessed the overall output of the matching. Using our method, 106 papers must be assigned to 46 reviewers, that means a ratio of 2.3 papers per reviewer. Considering the operation defined in Eq. 4 (Section 3.3, Step 3), an overall score was assigned to each paper-reviewer couple. This score, which is an aggregation of the partial scores: topic interest coverage, availability, recency, and quality, gives us a grade about the adequacy of each selected couple. Globally, this overall score is in the range [0, 1]. Considering the 212 assignments (2 reviewers per paper), the average overall score is 78.9% with the minimum fixed to 65% and maximum equal to 93.3%. The distribution of this overall score is depicted in Fig. 2. As it can be seen, score values were significantly high, with the first quartile at 73.5% and the third quartile at 83.4%.

5.2. The Reviewers Perspective

Second, we compared the reviewer to paper assignments with the quality index (QI) defined in Sidiropoulos and Tsakonas (2015). This measure represents the average percentage match between a reviewer's topics and the topics of each paper to which he/she has been assigned. As can be seen from the Fig. 3, out of the 46 assigned reviewers, approximately 10% had a QI of 50% and 90% had a QI above 50%. Of the latter group, 25% achieved a QI of 100%.

5.3. The Papers Perspective

Third, on a paper basis, we assessed the coverage of each paper's topics according to the assigned reviewers. We evaluated this measure in two parts. Using the assignments made by the system, we compared the topic coverage of each paper based on
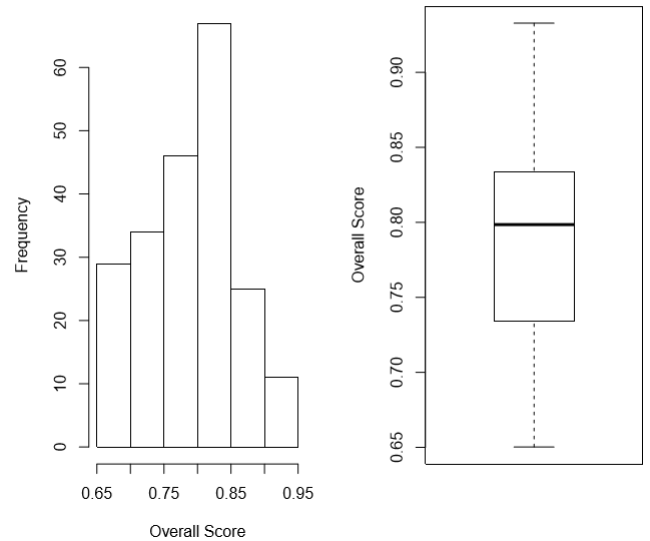

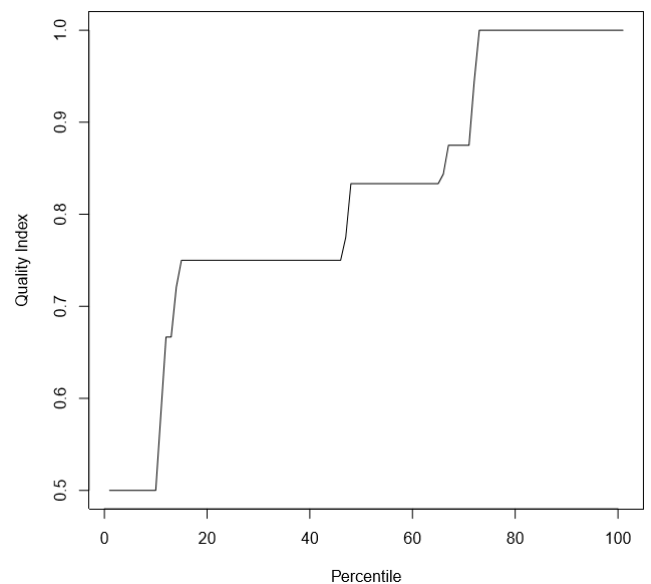**Fig. 2. Distribution of the overall score per assignment defined in Eq. 4, with $nr = 2$**

Fig. 3. Distribution of Quality Index of papers, $nr = 2$

the paper and reviewer topics assigned by the system. Next, we compared the topic coverage with the paper and reviewer topics determined by an expert.

Applying the reviewer and paper profiles determined by the system we obtained the following results. Out of the 106 assigned papers, 104 had a complete match. We define a complete match as one where at least one topic of each reviewer assigned matches the topics of a paper. In addition, we observed that 2 of the papers had a partial match. We consider a partial match to be a paper having only one reviewer having topics that match the paper. There were no papers without a match. In other

words, there were no papers where a reviewer assigned to a paper did not cover at least one topic of the paper.

5.4. The Expert's Opinion Perspective

In order to compare the results to that of an expert, a grounded truth was created similar to (Karimzadehgan et al. (2008)). An expert from the Artificial Intelligence community in Catalunya was consulted for the validation process. He assigned research topics from the CCIA conference to each of the Scientific Committee members. Then, he read the abstracts of each paper submitted to the conference and assigned relevant CCIA conference topics to each paper. This gave us a gold standard to evaluate our system.

Applying the reviewer and paper profiles determined by the expert we obtained the following results. Out of the 100 assigned papers (6 papers were discarded by the expert due to their minimal relation with CCIA topics), 81 had a complete match. In addition, we observed that 17 of the papers had a partial match. There were 2 papers without a match. Results showed that with the expert opinion the matches between papers and reviewers slightly decreased. We attribute the decrease to the more accurate assignment of topics to reviewers and papers by the expert, thanks to his knowledge about the reviewers.

6. Conclusions and Future Research

In this paper, a new method for assigning papers to reviewers for conferences has been introduced. This methodology improves existing systems because:

- It uses several sources of public information to define reviewers expertise profiles.

- It considers the whole set of papers submitted to the conference to define the most appropriate topics for each paper.

- The matching process is defined via the concept of coverage and uses an OWA operator, which allows us to avoid filtering but simultaneously consider several relevant variables for the process.

We are considering different lines for future research. We plan to compare the proposed method in three directions. Firstly, we would like to apply the method to a larger conference environment. Secondly, we will compare our results with the ones obtained by means of a classic optimization method. Lastly, we aim to apply a similar methodology to the human resources problem that considers the assignment of candidates for a job position.

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