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A COMPREHENSIVE SURVEY OF THE REVIEWER ASSIGNMENT PROBLEM

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Reviewer Assignment Problem (RAP) is an important issue in peer-review of academic writing. This issue directly influences the quality of the publication and as such is the brickwork of scientific authentication. Due to the obvious limitations of manual assignment, automatic approaches for RAP is in demand. In this paper, we conduct a survey on those automatic approaches appeared in academic literatures. In this paper, regardless of the way reviewer assignment is structured, we formally divide the RAP into three phases: reviewer candidate search, matching degree computation, and assignment optimization. We find that current research mainly focus on one or two phases, but obviously, these three phases are correlative. For each phase, we describe and classify the main issues and methods for addressing them. Methodologies in these three phases have been developed in a variety of research disciplines, including information retrieval, artificial intelligence, operations research, etc. Naturally, we categorize different approaches by these disciplines and provide comments on their advantages and limitations. With an emphasis on identifying the gaps between current approaches and the practical needs, we point out the potential future research opportunities, including integrated optimization, online optimization, etc.

Keywords: Reviewer assignment; information retrieval; optimization.

1. Introduction

Peer review, while attracting some controversy[1–5] is generally accepted as the best method available for validating research results before publication. As new technologies (e.g. E-print and Internet) are embraced by publishers, attempts at improving the current model are enabled, including online peer review via Internet,[6] open and signed review,[7] a secondary level peer review such as the UK's research assessment exercise,[3] information transparency,[8] etc. However, few attempts have changed the fundamental peer review process. One that has is the *community-wide review model*. For example, the Los Alamos pre-print server (http://arxiv.org) created by Ginsparg in 1991, allows the physics community to exchange un-reviewed preprints and refereed postprints electronically. It allows the rapid distribution of research results. However, it is not yet clear whether this experiment is succeeding. Peer review is regarded as the invisible hand that maintains the publication quality.[9]

Therefore, *refereed journal literature needs to be freed from both paper and its associated production costs, but not from the process of peer review*.[9]

There is a series of stages within the peer review process that ultimately leads to a referee review. Bence and Oppenheim[3] outline and compare the stages in traditional peer review and web-based peer review processes. In both types of peer-review processes, the first and potentially the most important stage is the one that attempts to distribute submitted manuscripts to competent referees. In this paper, we formally call it *reviewer assignment*. Clearly, this stage directly influences the resultant review and the quality of the publication. Ultimately, it will hurt the reputation of the journal or conference. To promise a proper review result, the reviewer assignment decisions have to take several issues into consideration. First, for each submitted paper, the assigned referees are expected to be the ones who are the most competent to do the work. Second, the referees should be interested in the paper, and willing to review them on time. Third, the reviewers' workload should be balanced, no reviewer should get more than a previously agreed upon number of papers, and each reviewer should get approximately the same number of papers if possible. Last but not the least, conflict of interest between reviewer and author should be acknowledged and avoided.

There are many possible ways of undertaking the reviewer assignment process. For journal submissions and some types of grant proposals, it is routinely done manually by editors or associate editors. Manual assignment relies heavily on the editors' knowledge on the most updated academic developments related to the topic. However, for conference submissions, where the review is required under severe time constraints and the submissions always arrive at the last minute, manual reviewer assignment is difficult. Some large scientific communities [e.g. Association for the Advancement of Artificial Intelligence (AAAI)] ask reviewers to bid on manuscripts. Ideally, a referee bid states the referee's subjective opinion of their expertise as regards to a particular submission. After all referee bids are collected, the conference organizers distribute each submission to a set of competent referees by matching algorithms.[10] Such a bid mechanism is studied by Ref. 11 using the data from the 2005 Joint Conference on Digital Libraries (JCDL). The paper shows that the submission subject domain and referee expertise are not the only factors involved. It implies that there are other factors (such as collaboration and friendship) beyond scientific merit that may influence referees to bid for particular submissions. Therefore, automatic reviewer assignment mechanisms are called for to deliver a fair and efficient assignment. Attempts have been made to use automatic tools to facilitate reviewer assignment. For example, Dumais and Nielsen[12] provides an automatic method for reviewer assignment for the Hypertext'91 conference. Most conferences in Computer Science are using commercial conference management systems to handle the reviewer assignment problem.[13]

An excellent survey on these commercial systems can be found in Ref. 14. This paper focuses on the methodologies in the academic literature rather than in these commercial systems. Regardless of the way reviewer assignment is structured, the process can be explicitly or implicitly divided into three phases:

(i) search reviewer candidates,
(ii) compute the degree of match between each manuscript and each reviewer candidate, and,
(iii) optimize the assignment.

In phase (i), a list of candidates of qualified reviewers should be generated. These candidates need not be the most competent to the submitted manuscript but there must be a sufficient level of relevance. For example, the committee members of a conference can be regarded as a shared candidate list of qualified reviewers. In this phase, we are especially interested in two issues. One, what are the criteria for researching the candidate reviewers? Two, how can we pick up relatively qualified candidates? In phase (ii), given the reviewer candidate list, we should compute the degree of match between the manuscript and the reviewer. The degree of match is a measurement of the similarity between the content of the manuscript and the expertise of the reviewer. In phase (iii), given the computed matching degrees, a feasible and optimal assignment can be performed. The assignment has to take many practical constraints into account. For example, workload balance, authors' preferences, etc. In this phase, we are especially interested in the modeling aspect.

This paper surveys related research in each phase. The boundary between any two consecutive phases is not always clear. Some researchers do not explicitly separate phases (i) and (ii), as they apply the matching degree computation to identify the potential reviewer candidates. Others may address the same issue in different phases. For example, the issue of conflict-of-interest may be examined in phase (i) or it can be addressed in phase (ii). Some methods may even address it in phase (iii). There are few surveys which provide a comprehensive review of all three phases. For example, Goldsmith and Sloan[15] is an excellent survey, but it focuses on techniques in phase (iii) only. This paper is the first one that provides a reasonably comprehensive survey of all three phases, with an emphasis on identifying the gaps between current approaches and the practical needs, while pointing out the opportunities for future research.

Reviewer Assignment Problem (RAP) is a growing multi-disciplinary research topic that integrates aspects of computer science, artificial intelligence, operations research, etc. Our research indicates that there are 36 publications investigating the three phases of RAP. Table 1 summarizes the number of publications by year of publication. The increasing number of publications in recent years indicates the growing importance of this topic.

Table 2 summarizes these publications by the type of publication. It shows that artificial intelligence (e.g. AAAI), computer science (e.g. ACM and IEEE), decision science (e.g. decision support system and Expert Systems with Application), and operations research are the four main academic communities which are interested in RAP. However, we find that the majority of publications on reviewer search

Table 1. Publications by year of publication.

Discipline	Total	1992–1998	1999–2002	2003–2005	2006–2008
Reviewer searching	14	1	2	5	6
Matching degree computation	12	3	5	2	2
Assignment optimization	10	0	3	3	4

Table 2. Publication statistics by type of publication.

Phase	Total	AI	CS	DS	OR	Interface	Others
Reviewer search	14	4	6	2	—	—	2
Matching degree computation	12	2	5	—	2	2	1
Assignment optimization	10	2	1	3	2	1	1

Note: AI is the Artificial Intelligence; CS is Computer Science; DS is Decision Science; OR is Operations Research.

and matching degree computation belong to the artificial intelligence and computer science fields, while the majority of publications on assignment optimization belong to operations research. Approaches in these two domains are seldom integrated. In our study indicates that there is only one paper performed the assignment by minimizing the sum of term weight difference generated by data mining.[16]

The remaining of this paper is organized as follows: Section 2 provides a review on the search for reviewer candidates. Section 3 presents methods in matching degree computation between manuscripts and reviewers. Section 4 presents models and algorithms for performing reviewer assignment optimization. We conclude the paper with suggestions for future research in Sec. 5.

2. Reviewer Candidate Search

For conferences and research agencies, the papers or research proposals are clustered in tracks or panels. For each track or panel, a number of potential external reviewers are recommended. Due to heavy workload or tight schedule, the invited reviewer may not accept this task. Therefore, it is necessary to generate a reviewer candidate list.

Explicitly or implicitly, it is the keyword that serves as the primary searching criterion. For journals and conferences, the authors are usually required to select keywords from a list. When the discipline information is hard to be represented by several keywords, data mining and information retrieval technology are used to exact the keyword-list by conducting unsupervised clustering[17,18] or supervised learning with previously accepted papers as the training set.[19]

Theoretically, the provided keywords or extracted keywords would make it possible to select the potential referees from a constructed knowledge base. One possible way is to use a digital database of scientific content. These databases use one of two major data acquisition methods: (i) manual insertion by volunteers (e.g. DBLP); (ii) automated harvesting of open-access databases, home pages of authors, web sites of the publication venues, and so on (e.g. CiteSeer,[20] Google Scholar, Windows Live Academic). This provides a relatively large set of choices. However, some deep web site such as PubMed, PubChem, and Science.gov, which have been estimated to contain 400–500 times more public content than the *surface Web*,[21] is largely invisible to current search engines. Some researchers have proposed systems which aggregate information from a variety of sources and provide added value to communities of researchers.[21] Despite of publicly available knowledge bases, some conferences and research agencies prefer to select the reviewers from published authors or successful grant applicants. For example, National Science Foundation (NSF) uses people who have submitted to NSF to join a reviewer pool. This limits the choices, but guarantees some degree of eligibility since it is thought that *those eligible to apply to NSF are eligible to review*.[16]

Professional level is an important measurement for qualifying potential reviewers. Sun *et al.*[22] summarize the five criteria for experts who review research proposals: keywords, publications, research projects, historical performance, and other experts' opinions. Figure 1 presents the explanation of criteria and their attributes. For journals and conferences, research projects might not be an important criterion. In practice, the professional level is mainly evaluated or estimated by editors or organizers. Research agencies are using some scientific approaches for evaluating the experts' professional levels.[22–25] The fundamental idea is to score the reviewers' qualification according to his/her historical records in these criteria.

One important issue, and sometimes a difficult one, is to identify the conflicts of interest relationships among potential reviewers and authors of scientific papers. The most recent work in this domain was carried out by Ref. 26, where they describe a semantic web application that detects conflict of interest. The degree of conflict of interest between the reviewers and authors is calculated based on a populated ontology. As input they integrated entities from two social networks, namely "knows" from a FOAF (Friend-of-a-Friend) social network and "coauthor" from the underlying co-authorship network of the DBLP bibliography. This permits the detection of more potential conflict of interests than the simplified method as implemented in Ref. 27. Analysis utilizing the semantic web appears to be a promising tool for identifying conflicts-of-interest.[28–30]

3. Matching Degree Computation

Given a set $P = \{1, \ldots, |P|\}$ of manuscripts and a set $R = \{1, \ldots, |R|\}$ of reviewers [which is available after phase (i)], we use c_{ij} to denote the matching degree of manuscript i for reviewer j, where $i \in P$ and $j \in R$.

Matching degree computation might be the most important phase for RAP. The matching degree measures the fitness of a manuscript and a reviewer. The fit

Criteria and related attributes		Description
keywords		Each of the external experts is requited to declare two keywords to indicate the discipline arrears he/she belongs to.
Publications	Time distribution	When had experts published their papers? It should reflect whether experts are active researchers or not.
	Quality	How about the quality of expert publications? It is often measured by the grade of journals in which papers are published.
	Quantity	How many papers had experts published in different grades of journals at different time?
Projects	Time distribution	When had experts undertaken R&D projects? It should reflect whether experts are active researchers or not.
	Quality	How about the quality of R&D projects that experts had undertaken? It is often measured by the grades of research projects.
	Quantity	How many R&D projects had experts undertaken with different grades at different time?
Historical performance in project selection	Time distribution	When had experts participated in research proposal evaluation? It should reflect whether experts are active evaluators or not.
	Quality	What're the grades of research projects that experts evaluated?
	Evaluation accuracy	IT is measured by the different between experts' evaluation and the final decision on a research proposal.
Other experts' opinions		Other experts' opinions on the professional level of the expert candidates. Combine this subjective information with the objective information above in order that experts can be evaluated adequately and accurately.

Fig. 1. Criteria and their attributes to evaluate experts.
Source: Sun *et al.*[22]

is estimated by two key criteria: the correlation of reviewer expertise and manuscript topic, and the conflict of interest between them. There are two approaches to matching degree computation: one is the discrete rating; and another one is information retrieval.

3.1. *Discrete rating based on reviewer preference*

The simplest answer to the question of whether manuscript and reviewer match is "Yes" or "No". Mathematically, for reviewer i and manuscript j, we can define

$$c_{ij} = \begin{cases} 0, & \text{if manuscript } i \text{ and reviewer } j \text{ cannot be matched;} \\ 1, & \text{otherwise.} \end{cases}$$

The authors are usually required to provide keywords of the submission, and reviewers represent their expertise in the same way. Once there is at least one keyword in common, and no conflict of interest, manuscript i and reviewer j are validated to be matched, then c_{ij} is set to be 1, otherwise 0.

As this approach is an oversimplification. Discrete rating is preferred by many to allow taking reviewer preferences into consideration. Discrete rating represents the matching degree in a range from 0 to 5, or 0 to 10, with higher rates representing higher degree of match. In a bidding model, the reviewers rate their preferences on a submitted manuscript based on a quick review on its abstract. The organizer will then examine for conflict of interest. If a conflict of interest is identified, the matching degree will be 0. This approach is exhaustive as each reviewer has to go through all the abstracts. Hence, it is only applicable in situations where there is a small number of submissions.

Some conferences define a property set $I = \{1, \ldots, |I|\}$ to depict each relevant subtopic or area of interest. In the case of the Metaheuristics International Conference 2005 (MIC 2005), the set includes 51 properties including Guided Local Search, Evolution Strategies, etc. Congruent properties can be used as vehicles to matching paper and reviewer. Instead of rating for all manuscripts, each reviewer is required to present his or her expertise level only on the matched properties. The property values are then defined for manuscripts and reviewers. Let as e_{ik} be the property value for manuscript i to property k, which is assigned the values "unacquainted", "neutral" or "familiar" (1, 2, 3, respectively), and the property value e_{jk} for reviewer j to property k is defined in the same manner. For a pair of property values, we can define a utility value. For example, if $e_{ik} = 3$ and $e_{jk} = 3$, we can define $m_{ij} = 3$. For a pair of $e_{ik} = 1$ and $e_{jk} = 1$, we can define $m_{ij} = 0$. Eventually, we get a 3×3 matrix $M = (m_{e_{ik}, e_{jk}})$ as below:

$$M = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 2 \\ 0 & 2 & 3 \end{bmatrix}$$

Thus, the matching degree c_{ij} is given:

$$c_{ij} = \sum_{k \in I} m_{e_{ik}, e_{jk}} . \tag{3.1}$$

This approach was used in Ref. 31. Its success depends on the definition of property, as well as the setting of property values and utility values. For example, m_{ij} in matrix M is sometimes set to a negative value in order to penalize assignments in which reviewer receives unacquainted papers.

In above approach, researchers implicitly assume that properties are independent without correlation. Hartvigsen *et al.*[32] proposed a method which explicitly considers the similarity among the properties. This method starts by giving reviewers and authors each 10 points to distribute over the standard properties, i.e, $I = \{1, \ldots, |I|\}$ to characterize the reviewer's expertise or the submission. In this way for each manuscript i and reviewer j, a classification vector is obtained:

$$P_i = (P_i(1), \ldots, P_i(|I|)), \quad i \in P, \tag{3.2}$$

$$R_j = (R_j(1), \ldots, R_j(|I|)), \quad j \in R. \tag{3.3}$$

Note that,

$$\sum_{k \in I} P_i(k) = \sum_{k \in I} R_j(k) = 10, \quad i \in P, \ j \in R. \tag{3.4}$$

The estimated numbers w_{kf} for $k \in I$ and $f \in I$, denote the degrees of similarity between each pair of properties. A larger number indicates a higher degree of similarity. (The degrees of similarity are drawn from 0 to 5 in the work of Ref. 32.) The matching degrees c_{ij} are found as solutions to the following linear program:

$$c_{ij} = \max \sum_{k \in I} \sum_{f \in I} w_{kf} y_{kf}, \tag{3.5}$$

$$\sum_{f \in I} y_{kf} = R_j(k), \quad k \in I, \tag{3.6}$$

$$\sum_{k \in I} y_{kf} = P_i(f), \quad f \in I, \tag{3.7}$$

$$y_{kf} \geq 0. \tag{3.8}$$

From the above linear program can be converted to transportation problem which can be solved in polynomial time.[33] The solution relies on the estimated weights w_{kf} which can be computed as a rounded average of one or more expert estimations.

The above approaches depend on the reviewer's preference, expert's estimations or the editor's knowledge. An information retrieval approach, belonging to the artificial intelligence domain, can provide more sophisticated solutions.

3.2. *Information retrieval approach*

Information retrieval is finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers).[34] It is the science of searching for documents, for information within documents and for metadata about documents. In addition, it is the science, of searching relational databases and the World Wide Web. Previous work in the area of assigning manuscripts to reviewers had approached the problem as one of information retrieval. For example, Cohen and Kjeldsen[35] proposed an expert system with information retrieval technology to help funding agencies to evaluate the pertinence between their goals and submitted research proposals.

Table 3 summarizes the main publications on methods belong to the information retrieval approach. All methods can be classified into three groups: content-based filtering, collaborative filtering, and hybrid.

Table 3. A statistics summary on information retrieval approach.

Study	Methodology	Techniques
Dumais and Nielsen[12]	Content-based	Latent semantic indexing
Yarowsky and Florian[37]	Content-based	VSM/naive bayes classifier
Basu *et al.*[52]	Hybrid	N/A
Popescul *et al.*[54]	Hybrid	N/A
Watanabe *et al.*[46]	Collaborative filtering	Scale-free network
Hettich and Pazzani[16]	Content-based/Optimization	Data mining
Rodriguez and Bollen[47]	Collaborative filtering	Relative-rank particle-swarm algorithm
Biswas and Hasan[19]	Content-based	VSM (Comparison study)
Cameron *et al.* (2007)	Hybrid	Semantic web

3.2.1. *Content-based information retrieval*

One of the earliest papers in the literature focused on reviewer assignment is the work of Ref. 12. The authors used data provided by 15 members of the reviewing committee for the HYPERTEXT '91 conference. These reviewers not only submitted abstracts of their interests and/or publications, but also provided complete relevance assessments for the 117 papers submitted to the conference. Using the information retrieval method known as LSI,[36] each document was represented by a matrix containing nearly 100 item vectors of factor weights which was computed automatically; each reviewer's expertise was evaluated in the same way. The matching degree between manuscript and reviewer was computed as the dot product of the two matrixes. Then, the submissions were ranked from most to least similar to each reviewer by matching degree. Each reviewer was assigned to the top n papers and another n from top $4n$ in his ranking list (the situation of assigning the top $2n$ papers directly to reviewers was also discussed in this work). Compared to random assignment, the authors found that the reviewers' mean relevance rating was greatly improved.

Similar work was performed for ACL'99 conference by Ref. 37. The authors used 92 electronic submissions (51% of the general manuscripts), and solicited representative papers from committee members, augmenting the collection with other papers downloaded from online sources. Let $V = 1, 2, \ldots, |V|$ be the set of keywords and $L = 1, 2, \ldots, |L|$ be the set of committees. Let R_l be the reviewers in committee l. The content-based approach used in this paper was the Salton-style vector space model (VSM),[34] which represented both the manuscripts and reviewer papers in the space $[0, +\infty)^{|V|}$ (i.e. there were $|V|$ vectors corresponding to $|V|$ different keywords). Note that the keyword-vectors could not only be obtained from knowledge database, but could also be generated by a set of training papers.

The main algorithm first computes a centroid $D_{i,k}$ for paper i and keyword k:

$$D_{i,k} = o_{i,k} \cdot w_k, \tag{3.9}$$

where $o_{i,k}$ is the number of occurrences for the kth keyword in paper i and w_k is the normalization weight associated to the kth keyword. One typical definition of the normalization weight is $w_k = \log(|P|/|P_k|)$, where $|P|$ is the total number of papers and $|P_k|$ is the number of papers that contain the kth keyword. We use D_i denote the vector $\{D_{i,k} : k \in V\}$

A centroid for each reviewer j and keyword k is computed in a similar way:

$$E_{j,k} = \sum_{i \in P} r_{ij} \cdot o_{ik} \cdot w_k, \tag{3.10}$$

where r_{ij} is the relevance weight for paper i and reviewer j.

A centroid $D_{l,k}$ for each committee l and keyword k is computed as the sum of its reviewer centroids [shown as Eq. (3.11)].

$$F_{l,k} = \sum_{j \in R_l} E_{j,k}, \tag{3.11}$$

we use F_l denote the vector $\{F_{i,k} : k \in V\}$

Then, each paper is classified (assigned to a committee) by choosing the highest ranking, based on a computation of its cosine similarity [shown as Eq. (3.12)] with the committee centroids:

$$\begin{aligned} \text{cosine} - \text{similarity}(F_{l,k}, D_{i,k}) &= \frac{\sum_{k=1}^{|V|} F_{l,k} \cdot D_{i,k}}{\sqrt{\sum_{k=1}^{|\nu|} F_{l,k}^2} \cdot \sqrt{\sum_{k=1}^{|V|} D_{i,k}^2}} \\ &= \left\langle \frac{F_l}{\|F_l\|^2}, \frac{D_i}{\|D_i\|^2} \right\rangle . \end{aligned} \tag{3.12}$$

To avoid using a high dimensional vector space to represent the whole document collection, prototype-matching language and an independent clustering system were used by Ref. 38. This approach can keep much information from each document's original text without document collection. However, it is not clear that whether this approach can achieve satisfactory results.

Content-based information retrieval, also known as content-based filtering, is a popular method in the early research of reviewer assignment. One drawback of this approach is that the costs associated with text analysis on a large data set could be beyond most budgets. For conferences, when the number of reviewer candidates is small, it may be applicable. However, for classic journal peer review and open commentary peer-review, where the number of potential reviewers would be large, the mentioned algorithms have not been used.

3.2.2. *Collaborative filtering*

Content-based information retrieval looks only at the contents of an artifact (e.g. the words on paper), while collaborative filtering considers the opinions of other like-minded people in respect to these artifacts. Collaborative filtering has been used to recommend NetNews articles,[39] movies,[40,41] music,[42,43] and even jokes.[44] Those techniques have been successfully implemented in E-commerce.[45]

Watanabe *et al.*[46] proposed and implemented a collaborative filtering method using "scale-free" network, where the vertices represent keywords of reviewers' expertise and their papers' topic. Suppose one vertex represents the keyword k of paper i, say (i, k), in the network is assigned a fitness parameter η_{ik} and any edge connected to vertex (i, k) is assigned a weight parameter w_{ik}. Whenever a new vertex (i, k) with a fitness η_{ik} is added to the network, this new vertex is connected with edges to the vertices already in the network, and the probability of connecting to a vertex (i, k) is proportional to the degree and fitness of vertex k by the following Eq. (3.13).

$$\pi_{ik} = \frac{\eta_{ik} w_{ik}}{\sum_{k \in V, i \in P} \eta_{ik} w_{ik}}. \tag{3.13}$$

The scale-free network is initially constructed with reviewers' representative papers. Then, a large amount of papers from a training database are added to augment the network. The matching degree c_{ij} between manuscript i and reviewer j is proportional to the sum of similarity for keywords appearing in them, where n is the number of keywords that appeared in manuscript $i's$ topic and reviewer $j's$ expertise/interest.

$$c_{ij} = \frac{1}{|V|^2} \sum_{k \in V} \sum_{k' \in V} \pi_{ik} \pi_{jk'}. \tag{3.14}$$

Equation (3.14) allows calculation of the similarity between manuscript i and reviewer j, π_{ik} is the value of keyword k that appeared in manuscript i mentioned in Eq. (3.13).

The scale-free network still focuses on the collaborative information in the contents. The co-authorship network looks at the collaborative information in the manuscript's reference and its collaborative authors, and online collaborative publication. Rodriguez and Bollen[47] proposed a collaborative filtering approach where a co-authorship network was defined by a triple graph composed of nodes, edges and weights. Vertices represent scholars in the network, edges represent a joint publication between two authors, and weights represent the strength of the relationship between any two collaborating authors. They apply a fairly sophisticated particle-swarm algorithm to compute the matching degrees. Similar work can be found in Refs. 48 and 49.

3.2.3. *Hybrid approach*

As both content-based and collaborative methods use data that are orthogonal to one another, hybrid approaches that use combinations of the data are popular in recommendation systems. WebWatcher and Fab being cases in point. As hybrid systems exploit data from multiple sources with the expectation of doing better by compensating for the limiting factor of data sparseness associated with any single source, researchers attempt to apply hybrid systems to RAP.

Popescul *et al.*[50] proposed a unified probabilistic framework for combining content-based and collaborative information retrieval by extending Hofmann's[51] aspect model to incorporate the information source among scholar, manuscript and manuscript content. Matching degree is interpreted as a likelihood. These three data sources were conjunctive as the conditional probability for each other. Then the joint probability of these three is computed from the conditional probability. Then the likelihood can be computed as the sum of conditional probabilities.

Basu *et al.*[52] proposed a hybrid approach of paper recommendation combining multiple information sources garnered via web mining techniques. They collected information about reviewers from the web (e.g. reviewers' homepage, online published papers, etc.), and deconstructed reviewer interest and paper contents into information sources, and then combined the information sources using different query formulations. Their framework provided a more flexible alternative to simple keyword-based searches and a less intrusive alternative to collaborative methods. In addition, they compared two ways of formulating queries using content-based information retrieval and one collaborative approach, and found that the recommendation algorithm using conjunctive queries outperforms other approaches.

Hettich and Pazzani[16] described an approach deployed at the U.S. NSF for assisting program directors in identifying reviewers for proposals. First, proposals were represented in the standard TF-IDF vector space of all words in the document collection; the 20 terms with highest TF-IDF weights would illustrate the representation for the proposal. Then, with the published papers from online databases, reviewer's expertise was represented in the same way as the proposals. Conflict of interest and potential reviewers were identified at the same time. Data mining techniques were then used to sort proposals into clusters, and the cosine similarity was computed between each proposal's term vector and each cluster's term vector as it is presented in Sec. 3.1. Wherever a proposal was not assigned to the most similar cluster, a signal would be sent to the program directors with a suggestion to move the proposal. Then the assignment of proposals to reviewers was done within cluster.

Though information retrieval techniques have achieved impressive success in E-business,[53] the application of search engines (especially experts search) and recommendation systems, in the RAP domain is still at an early stage.[54]

4. Reviewer Assignment Optimization

In most cases, manuscripts are required to be assigned to the reviewers under the following conditions:

(i) each manuscript should be assigned to a certain number of reviewers, a_i, which is set by the organizer or the editor;
(ii) as much as possible, each manuscript should be assigned to reviewers who are experts in the area. A given threshold T can be set to identify reviewers' qualification;

(iii) each reviewer should be assigned to no more than a certain number of manuscripts, b_j, which can be set by the organizer or the reviewer himself;
(iv) each reviewer should be assigned to approximately the same number of manuscripts, in order to balance their workload.

This problem can be viewed as an enhanced version of the Generalized Assignment Problem (GAP)[55] which is widely applied in optimization applications where two large sets of objects need to be matched such that each object in one set gets assigned to a small number of objects from the other. There are many practical applications, including but not limited to:

(i) Resource allocation: Matching funding agencies to research projects,[35] scheduling on parallel machines,[58] assigning managers to construction projects,[59] classroom assignment.[60]
(ii) Staff scheduling: Assigning graduating students to interviewers, assigning press releases to newspaper reporters, matching staff to projects in consulting companies,[59] crew scheduling in airlines,[61,62] posting servicemen.[63,64]
(iii) Decision making: Corrective action recommendation for construction material management.[65]

Table 4 summarizes the main works of reviewer optimal assignment. The models can be classified into three groups: GAP formulation,[56] Network flow model and Set-covering model.[57]

4.1. *RAP formulation*

With the matching degree matrix C, a binary variable x_{ij}, whose value is 1 if manuscript i is assigned to reviewer j and 0 otherwise, RAP is formulated by the following Integer Programming (IP) formulation:

$$\max \sum_{i\in P}\sum_{j\in R} c_{ij}x_{ij}. \tag{4.1}$$

Table 4. A statistics summary on review on the RAP optimization.

Study	Model	Algorithm
Benferhat and Lang[67]	GAP (IP)	VCSP
Tian *et al.*[24]	GAP (IP)	N/A
Merelo-Guervos *et al.*[66]	GAP (IP)	Evolutionary
Merelo-Guervos and Castillo-Valdivieso[70]	GAP (IP)	Hybrid (Greedy/Evolutionary)
Cook *et al.*[72]	Set-Covering (IP)	Greedy
Janak *et al.*[56]	GAP (IP/MIP)	N/A (using CPLEX)
Goldsmith and Solan[15]	Survey	N/A
Sun *et al.*[22]	GAP (IP)	N/A
Schirrer *et al.*[31]	GAP (IP/MIP)/Network Flow	Memetic/(using XPressTM)

Subject to

$$\sum_{j\in R} x_{ij} = a_i \,. \tag{4.2}$$

$$\sum_{i\in P} x_{ij} \le b_j \,. \tag{4.3}$$

$$x_{ij} \le \left\lfloor \frac{c_{ij}}{T} \right\rfloor . \tag{4.4}$$

$$x_{ij} = 0, 1 \,. \tag{4.5}$$

The objective function (4.1) maximizes the total matching degree of the assignment. Alternative choices of objective functions can be found in Ref. 15. Constraints (4.2) and (4.3) ensure that condition (i) and (ii) are satisfied respectively. Constraint (4.4) along with (4.5) prevent a reviewer from being assigned to a manuscript whenever c_{ij} is smaller than the given threshold T. Constraint (4.6) instead of (4.4), is brought into the mathematical model to ensure that at least one reviewer whose matching degree for manuscript i is greater than or equal to T.

$$\max_{j\in R} \{c_{ij} x_{ij}\} \ge T \,. \tag{4.6}$$

When there are multiple property sets (or committees) are defined in the disciplines category (as presented in Sec. 2.1), the problem should be handled as three-dimensional assignment with the matching degree $c_{ij,l}$, where $l \in L$.[31] The mathematical model is given as:

$$\max \sum_{i\in P} \sum_{j\in R} \sum_{l\in L} c_{ij,l} x_{ij,l} \,. \tag{4.7}$$

Subject to

$$\sum_{j\in R} x_{ij,l} = a_{i,l} \,. \tag{4.8}$$

$$\sum_{i\in P} \sum_{l\in L} x_{ij,l} \le b_j \,. \tag{4.9}$$

$$\sum_{l\in L} x_{ij,l} \le 1 \,. \tag{4.10}$$

$$x_{ij,l} = 0, 1. \tag{4.11}$$

Constraint (4.8) ensures that each manuscript and each slot have exactly $a_{i,l}$ reviewers assigned. The parameter $a_{i,l}$ may be different from different l, as the organizing chairs pay different attention to different property sets. Constraint (4.9) guarantees that reviewer j is not assigned to more than b_j manuscripts. In addition, as a particular manuscript may belong to multiple property sets, it cannot be assigned to the same reviewer multiple times, which is prohibited by constraint (4.10).

The above model does not take into consideration workload-balance. This can be reduced to an instance of minimum network flow problem. The RAP can be

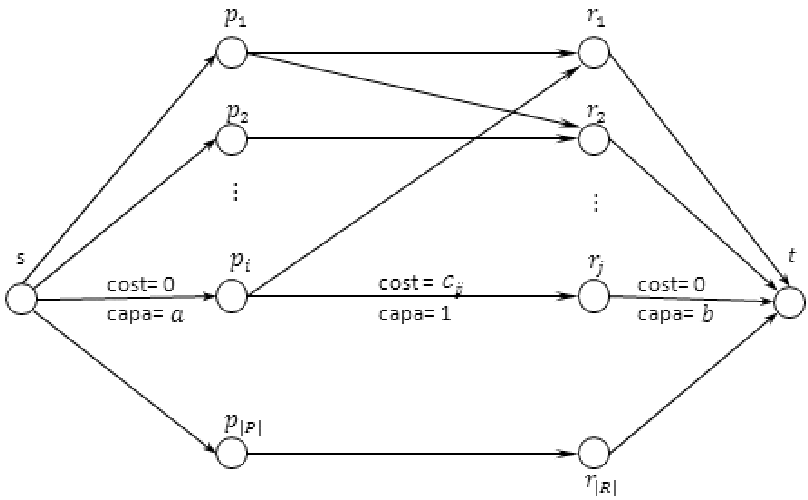

Fig. 2. Network flow version of RAP.

visualized as a network as Fig. 2. In the network, s is a source node, and t is a sink node. p_i is a set of nodes representing reviewers, where $i \in P$. And r_j is a set of nodes representing manuscripts, where $j \in R$. Any arc from s to p_i has a capacity a_i and cost 0. Any arc from p_i to r_j has a capacity 1 and a cost c_{ij} if reviewer j is qualified to review manuscript i, otherwise a capacity 0. Any arc from r_j to t has a capacity b_j and a cost 0.

Variations of the RAP network flow version have been suggested. Merelo-Guervos and Castillo-Valdivieso[66] introduced manuscript node p_i which can be represented by a_i nodes corresponding to the manuscript slots, and each reviewer node r_j by b_j nodes. Therefore, all the arcs from source to manuscripts and from reviewers to sink can be reset as capacity 1. When manuscripts are characterized by different property sets and every character of a manuscript must be covered, each manuscript node p_i can also be represented by l nodes if there are l property sets.

The threshold constraint (4.4) can be modeled by introducing an intermediate reviewer node r'_j which links with each reviewer node r_j. The capacity of linking arc is set to 0 when the condition $c_{ij} \geq T$ is not satisfied.[32]

The problem can then be solved as a maximum/minimum cost flow problem utilizing polynomial algorithms.[33]

4.2. *GAP formulation with work balance condition*

There are two efficient approaches to address the workload balancing issue. One is a multi-objective approach. The other is a relaxation approach.

Define ℓ_j as the total number of manuscripts assigned to reviewer j, and ℓ_j^* as the quantity set by reviewers or conference chair. Then define an imbalance penalty term η as the sum of the gap between reviewer ℓ_j and ℓ_j^* for each reviewer, e.g.

$$\eta = \sum_{j \in R} \left| \ell_j - \ell_j^* \right| . \tag{4.12}$$

By introducing a parameter, the problem in considering the workload balance can be formulated as a multi-objective problem:

$$\max \sum_{i \in P} \sum_{j \in R} c_{ij} x_{ij} . \tag{4.13}$$

Schirrer *et al.*[31] shaped this penalty term by raising a new parameter e_i for the review effort of manuscript i, which could be very different in structure and complexity. The manuscript effort e_i was estimated from characteristic qualities (such as page count, number of sub-problems treated, number of optimization methods, etc.) of the papers, which can be entered directly by the authors at submission. Then the imbalance penalty term yields as formula (4.14) and (4.15), where ℓ_j was the effort of reviewer j and ℓ_j^* was the mean of reviewers' effort.

$$\ell_j = \sum_{i=1}^{p} x_{ij} \cdot e_i . \tag{4.14}$$

$$\ell_j^* = \overline{\ell^*} = \frac{1}{|R|} \cdot \sum_{i \in P} a_i e_i . \tag{4.15}$$

Another approach is to relax the constraint 4.11. For example, Merelo-Guervos *et al.* (2003)[66] relaxed the constraints (4.11)–(4.14), and penalize those constraints in the objective functions of IP formulation:

$$\begin{aligned} \max \sum_{i \in P} \sum_{j \in R} c_{ij} x_{ij} &- \alpha \cdot \sum_{i \in P} \max \left\{ 0, a_i - \sum_{j \in R} x_{ij} \right\} \\ &- \beta \cdot \sum_{j \in R} \max \left\{ 0, \sum_{i \in P} x_{ij} - b_j \right\} . \end{aligned} \tag{4.16}$$

$$\sum_{l \in L} x_{ij,l} \geq a_{i,l} - 1 . \tag{4.17}$$

The parameter $\alpha \geq 0$ is the penalty weight for missing reviewers ($\alpha = 0.5$ in the work of Ref. 66), and $\beta \geq 0$ is for reviewers' excessive workload. These two control parameters provide flexibility for shaping the solution.

Benferhat and Lang ˜citeBenferhat-2001 provide a different vision of minimizing assignment disutility by aggregating five conditions into numerical disutility, including paper slot, reviewer's workload, conflict of interest, reviewer preference and topic. Reviewers and authors were asked to select topic (corresponding to discipline/keyword in above paragraphs) from a category, reviewers were required to express their preferences for each paper by scores 0, 1, 2, and 3. This approach, in some sense, can be interpreted as a specialized relaxation approach.

RAP is an enhanced version of Multiple Resources GAP (MRGAP), which is widely known as NP problem and has been studied extensively. Cattrysse and Van Wassenhove[68] gave a survey of algorithms for GAP. Branch-and-Price provided one of the best performing for the exact approaches algorithm of GAP.[69] Various heuristic and meta-heuristic approaches have also been proposed, including greedy method, depth search, taboo search, beam search, genetic algorithm and ant colony optimization. Besides these general approaches, researchers have proposed specific algorithms for RAP. Merelo-Guervos and Castillo-Valdivieso[70] proposed an evolutionary algorithm. A memetic algorithm was developed by Ref. 31 for the RAP model with workload imbalance penalization, based on the ideas of Ref. 71. However, those approaches are generally for GAP, very few of them are discussed in the context of RAP.

4.3. *Set-covering formulation*

The above RAP optimization models all consider how to assign manuscripts to reviewers and optimize the general objective according to matching degree. However, Cook *et al.*[72] emphasized the importance of pair-wise comparison in peer review, and approached the assignment by maximizing the number of manuscript pairs to be evaluated by one or more reviewers. The special approach was meaningful to the aggregation of partial rankings of subsets of proposals by different reviewers into consensus ranking. The mathematical model was presented as a set-covering integer programming formulation. Below is the notation system in the set-covering formulation:

- $\Re_j$: The collection of manuscripts subset, whose manuscripts reviewer j is qualified to review.
- H: The collection of all pairs of manuscripts $\{u, v\}(u \neq v)$ for which there is at least one reviewer who is qualified to reviewer both manuscripts.
- T_{uv}: The number of reviewers capable of reviewing the pair of manuscripts $\{u, v\}, (u \neq v)$.
- S: A subset that contains b_j manuscripts and $S \in \Re_j$.
- x_j^S: A binary variable, whose value is 1 if reviewer j reviews the manuscripts according to subset $S \in \Re_j$ and 0 otherwise.
- t_{uv}^h: A binary variable, whose value is 1 if the number of reviewers that review the pair of manuscripts (u, v) is exactly h and 0 otherwise.
- c_{ju}^S: An indicator parameter, whose value is 1 if the combination of reviewer j and manuscript u satisfy $u \in S$ for $S \in \Re_j$ and 0 otherwise.
- W^h: A weighted utility parameter associated with (the number of reviewers that review a certain pair of manuscripts). Its value should be selected as positive increasing series with decreasing difference series, namely $0 < W^1 < W^2 < \cdots$ and $W^h - W^{h-1} > W^{h+1} - W^h$ for all $h \geq 2$, note that W^0 is set to 0.

The set-covering integer programming model was given as:

$$\max \sum_{\{u,v\}\in H} \sum_{h=1}^{T_{uv}} W^h \cdot t_{uv}^h \tag{4.18}$$

$$\sum_{j\in R} \sum_{I\in\Re_j} C_{ju}^S \cdot x_j^S \geq \sum_{h=1}^{T_{uv}} h \cdot t_{uv}^h \quad \forall \{u,v\} \in H \tag{4.19}$$

$$\sum_{S\in\Re_j} x_j^S = 1 \quad \forall j \in R \tag{4.20}$$

$$\sum_{h=0}^{T_{uv}} t_{uv}^h = 1 \quad \forall \{u,v\} \in H \tag{4.21}$$

$$x_j^S, t_{uv}^h \in \{0,1\}\,. \tag{4.22}$$

The objective (4.18) maximizes the sum of weighted utility for each pair $\{u, v\}$. Constraints (4.19) define the relationships between the variable t_{uv}^h and x_j^S. Constraints (4.20) ensure that exactly one subset S is chosen for, and control the workload of each reviewer. Constraints (4.21) ensure that exactly one value of is associated with each pair. Constraints (4.22) define the binary variables. The proposition of an appropriate selection for W^h is presented, and the harmonic series $W^h = \sum_{i=1}^{h}(1/i)$ is suggested to be a good example.

This set-covering model can be solved by CPLEX. Numerical experiments show that for small and medium sized problems, CPLEX works well. However, for large problems, CPLEX is not capable of solving them within an acceptable length of time. Therefore, Cook *et al.*[72] proposed a greedy procedure which assigns the proposals to reviewers according to the priorities of the reviewer-proposal pairs. The priority rule considers the number of reviewers qualified to review each proposal as well as the remaining capacity. This greedy procedure can produce near optimal solutions for large size instances according to the numerical experiments.

5. Conclusion

We found that the works on RAP mainly focus on the issues in one phase or two phases. Our survey demonstrates a variety of methods for solving the issues in one particular phase or two. These methods, with years of continuous improvement, become mature enough to tackle problems in separate phases of practical size. However, we found that approaches for solving these phases are seldom integrated. In practice, if the optimization is restricted to the partial phases, the resulting optimal solution may not be satisfactory. For example, an optimal assignment based on a poor matching degree computation is far from a good solution for reviewers. Therefore, the need for integrated optimization is becoming more and more relevant. In the integrated framework, a mechanism for considering objective and subjective information together in an interactive decision making interface should be developed. Meanwhile, an integrated framework calls for evaluation benchmarks which are very essential for the development of this field.

In literatures, evaluation is usually made by comparing the proposed approach with random assignment or human assignment using actual data from some conferences.[12,26,37] The evaluation may rely on feedback from reviewers.[31] However, until now, there is no widely accepted benchmark test cases. Therefore, a set of well-designed testing cases are definitely needed. Good references include the Solomon's cases[73] for Vehicle Routing Problem and the Netflix Prize[74] case for data mining.

Further, the application of more advanced artificial intelligence techniques which have been successfully implemented in other fields (such as E-commerce, Search engines, etc.) should be examined. One example is the Non-Rating-Based approach. Currently, most approaches for matching degree computation are based on rating. Cook *et al.*[72] is perhaps the only one that emphasizes the importance of ordering-based rating in peer review. However, that study did not provide any method for generating the ordering but assumes the ordering as given. On the other hand, in movie recommendation systems, ordering-based collaborative filtering techniques have been attempted.[75,76] Another example is Multi-criteria Rating. Multi-criteria (or multi-component) rating systems are emerging in many industries. Restaurant recommendation systems, such as Zagat's Guide, provide three criteria for restaurant ratings (e.g. food, doctor, and service), e-Commerce websites,[77] such as Buy.com, use multi-criteria ratings for consumer electronics (e.g. display size, performance, battery life, and cost). Note that those multi-criteria rating systems typically are not used in the context of RAP.[78] It would be interesting to investigate whether we can interpret conflict-of-interest, qualification, and matching as multi-criteria, and then apply a multi-criteria ratings technique to identify the best matching reviewers and manuscripts.

Besides integration, online optimization is an important issue as well. In practice, the initial assignment decision is passed to the reviewers first. The reviewers decide whether to accept or reject the task. In case the reviewer rejects the task, new reviewers must be found and a new decision making process performed. In a time constrained environment, it would be beneficial to use re-optimization techniques to generate new solutions instead of re-doing the whole process. This deserves in-depth research as well.

A move from relatively theoretical publications to more practical ones can be seen. Both the artificial intelligence techniques and optimization methods are being applied more and more in real conference management[79–81] (e.g. CyberChair, ConfMan, AAA S/W, Puma, SIGACT, etc.).

Again, it would be interesting to investigate the implementation of RAP solutions within popular office toolkits. The previous research have been in response to the predicament in science community. Solutions for certain community problems are addressed using the corresponding methodologies of that field. As a result, professional knowledge and programming skills are required to implement solutions in literature, which result in the inconvenience to conference management communities. In this case, additional investment should been made to purchase or hire professional staff for specifying RAP software. Comprehensive RAP implementation based on office toolkits (e.g. MS Excel, MS Access, etc.) is greatly needed.

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