Convex Optimization for Reviewer Assignment in Conferences

Miguel Castaño Arranz[a]

[a]*Division of Operation and Maintenance, Luleå University of Technology, Luleå, 97752, Norrbotten, Sweden*

Abstract

An Artificial Intelligence (AI) for the Reviewer Assignment Problem (RAP) in conferences is introduced. The introduced AI for RAP consists of an Information Retrieval step and an Expertise Matching step. The main contribution of this paper is in casting a novel Convex Expertise Matching (ConvEM) scheme for large scale assignments. ConvEM is based on splitting the Expertise Matching problem in convex sub-problems with equal number of reviewers and papers. The introduced AI for RAP is tested in a conference with 3043 authors and 1360 papers. The performance of ConvEM is evaluated by comparison with a baseline greedy assignment. Finally, this paper discusses the large potential to adapt ConvEM to e.g., i) resolve RAP problems with author and reviewer quotas, and ii) incorporate other research results such as advances in Information Retrieval.

Keywords: Reviewer Assignment Problem, Peer Review, Electronic Publishing, Optimization, Artificial Intelligence, Information Retrieval

1. Introduction

Despite the long history of journal publishing, peer reviewing has come under increasing focus due to factors such as the revolution started in the 90's with the emergence of electronic publishing (see [1]). Electronic publishing has accelerated the publishing process and reduced costs (see [2]). During the electronic publishing revolution, multiple authors have conceptualized the future of academic publishing (see e.g. [3]), which is still under radical transformations.

The peer review process has been put under large scrutiny in the literature for reasons such as inconsistency, bias, abuse and inexperience of the reviewers (see [4]). Mitigating the inexperience of the reviewers is the mission of this paper. This is done by maximizing the quantified expertise of the reviewers assigned to the manuscripts.

According to the study in [5]: "*authors are satisfied with reviews whose comments they deem helpful, and when they feel that the reviewer has made an effort to understand the paper*". It is therefore of large importance to assign qualified reviewers to papers. An unqualified reviewer may reject a valid study or accept a faulty or fraudulent result (see [6]).

The peer review system is based on the assessment of original work by other people in the same domain (see [7]). In this paper, peer-review is considered to be composed by the following sequential phases performed by the review committee (see [8]) : i) receiving submissions, ii) sending submissions to reviewers, iii) collecting reviews, iv) making final decisions based on the reviews, v) sending final decisions to the authors.

The goal of this paper is to create an Artificial Intelligence (AI) to support the review committee in phase ii), which is sending submissions to reviewers. More explicitly, the introduced AI automates the assignment of papers to an available pool of reviewers. The posterior act of sending the review request has to be performed by the review committee with other means such as a conference management system.

The pool of reviewers often includes personal contacts, the Program Committee, and authors of submitted papers. The review committee may often have knowledge on the expertise of their personal contacts and the Program Committee. However, they review committee is not expected to know the expertise of all the conference authors. This knowledge gap hinders the exploitation of conference authors as reviewers. Assisting the review committee in exploiting the use of conference authors as reviewers is the focus of this paper.

The problem of assigning reviewers to papers is often referred in literature as the Reviewer Assignment Problem (RAP). RAP is often separated in two tasks: Information Retrieval (IR) and Expertise Matching (EM).

The AI introduced in this paper automatically generates review assignments for the authors of a conference. This is done by resolving the IR and EM tasks sequentially. IR extracts information on the expertise of the authors in the domain of each paper, as well as their conflicts of interest. This information is later used in EM to run an optimization scheme which generates review assignments for each of the authors.

An important contribution of this paper is the introduction of a new method for EM, which is formulated as a convex optimization problem and can be resolved efficiently. The method is hereby named Convex Expertise Matching (ConvEM).

The mathematical formulation of ConvEM is similar to other EM methods in the literature (e.g. [9]), where the expertise of the reviewers is maximized with constrains on: i) the number of assignments per reviewer, ii) the number of reviewers per paper and iii) conflicts of interest. The major novelty in this paper is in the decomposition of EM as a set of continuous Linear Programs which are convex and can be efficiently solved without the need of any approximations.

The introduced ConvEM is illustrated in a large-scale dataset with 3043 reviewers and 1360 papers. This is a very significant difference with the surveyed literature, where optimality has only been demonstrated in datasets with a maximum of 73 papers. In the surveyed literature, datasets of up to 338 papers have been addressed with the need of large approximations which deviate from optimality.

No similar method has been found in the literature which can be compared in a large-scale example. A Greedy Expertise Matching is implemented and used as baseline to perform a comparison.

This paper continues with a literature study discussing previous work in Section 2. For an overview on the rest of the paper and an overview on the introduced AI, the reader shall refer to Section 3.

2. Previous Work

This paper introduces methods for IR and EM, forming a complete AI for RAP. The introduced IR method can be substituted by other compatible methods existing in the literature. The main results of this paper are on introducing an EM method called Convex EM (ConvEM).

Compatible IR methods need to provide with a quantification of the expertise of reviewers in papers and with conflicts of interest. Examples of compatible IR methods found in literature are: i) parsing abstracts for searching keywords in [6], using the Vector Space Models in [10], and iii) searching for information in the personal web of the reviewers in [11].

The papers on IR cited above (see [6, 10, 11]), include an EM mehtod for illustration, which is based on ranking the best available reviewers for each individual paper. This type of EM is normally referred as Retrieval-based RAP (RRAP), and is not suitable for assigning simultaneously a pool of reviewers to a pool of papers (see [12]).

The Convex EM method introduced in this paper targets the automatic assignment of reviewers considering simultaneously all the available reviewers, their expertise, and the domain of the papers. This category of EM assignments are often referred in literature as Assignment-based RAP (ARAP) (see [12]). This review of previous work will therefore focus on EM methods for ARAP.

In [9], EM is formulated as an optimization problem which is resolved with two approaches: i) as an integer programming problem, or ii) using a greedy algorithm. Both approaches have large drawbacks: the former requires a combinatorial search which is often impossible in practice, and the latter leads to solutions which are often far from optimal and may violate the constrains. The integer programming approach has been demonstrated on a set of only 73 papers. It is also unclear how the solutions of the integer program have been sought, since assigning 73 papers to 73 reviewers leads to approximately 40 billion candidate solutions to be evaluated. Additionally, their optimization problem does not regulate the homogeneous distribution of papers to reviewers.

During literature investigations, it was found that even recent publications still approach EM as a combinatorial problem and demonstrate solutions only on very small datasets (e.g. up to 30 papers in [13]).

The application of EM to larger datasets is facilitated by the convexification of the problem. However, convexifications often result in approximations or reformulations which do not actually resolve the real problem. In [14], the convexification of the solution set means that the relationship between every reviewer and every paper will be assigned a real value between 0 and 1, with a 0 meaning that the reviewer will not review the paper and a value of 1 meaning that the reviewer will be assigned to review the paper. The optimal assignment will therefore have real values (e.g. 0.3) which cannot be put directly in practice. The algorithm has been tried on a medium size conference of 338 papers and 354 reviewers.

Other EM methods such as the introduced in [15] are based on logic rules and assign papers to reviewers one by one. These EM methods provide assignments which are expected to be far from optimality, but they can however be applied to larger datasets than those methods based on combinatorial solutions.

3. Overview

In this paper, a complete AI which assigns papers to reviewers in conferences is introduced. Significant results have been generated in all the blocks represented in Fig. 1. However, the main innovation is in EM. The innovation consists of splitting EM in convex sub-problems which can be efficiently solved. For a complete demonstration of this innovation in EM, the following has been introduced (see numbered boxes in Fig Fig. 1): i) a complete AI for RAP, ii) an alternative Baseline Greedy Assignment for comparison, iii) Performance Evaluation metrics to evaluate the introduced innovation by comparison with the baseline.

The AI for RAP introduced in this paper is described through sections 4-6. The AI resolves two tasks: IR and EM.

IR is discussed in Section 4. The goal of IR is to obtain information on the expertise of reviewers in the papers (Expertise Matrix) and to extract conflicts of interest (Veto Matrix). This extraction is done in 3 steps: 1) Gathering, 2) Inference, 3) Pre-processing.

EM is discussed in Sections 5-6. Expertise Matching is divided in two steps: I) mathematical formulation of EM as an optimization problem (see 5), and II) convex solution to the EM optimization problem (see 6).

During the mathematical formulation of EM in 5, the problem is described as a cost function to maximize subject to a set of constraints, leading to a large-scale combinatorial optimization problem.

Section 6 introduces the main novelty of this paper, which is splitting the combinatorial optimization problem in convex sub-problems. Each of the convex sub-problems can be resolved with a variety of efficient solvers such as the Hungarian algorithm. The solutions to each convex sub-problem are then aggregated.

In ConvEM, optimality is only guaranteed for each of the sub-problems. However, aggregating the solutions of the sub-problems is expected to lead in a satisfactory assignment which is close to the optimal and in very short computational time. A scientific evaluation of the solution will be performed using quality metrics and a comparison with a baseline solution. For this purpose, a baseline greedy assignment is introduced in 7. The quality metrics are given in Section 8. The comparison with the baseline is given in the case study in Section 9.

The introduced solution to the reviewer assignment problem has the potential to be extended for the generic case with reviewer quotas and paper

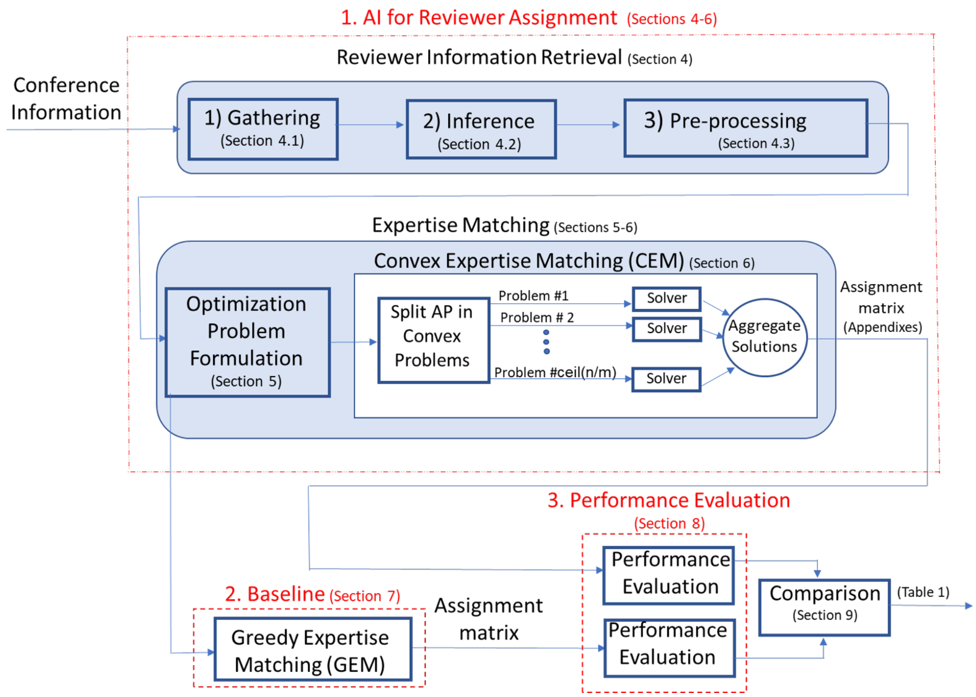

Figure 1: Overview of the methods introduced in this paper, including an AI for Reviewer Assignment.

quotas which is formulated in 5. Such potential extensions are given in Sec. 10.

The conclusions are given in 11.

Finally, the Appendix gives illustrative extracts from the assignment solutions of the case study.

4. Reviewer Information Retrieval

The introduced IR method is composed by three steps: 1) gathering, 2) inference, and 3) pre-processing.

Every author of the conference will be assigned a review task. Therefore, the terms *author* and *reviewer* will be used in interchangeably in the technical parts of this paper. The term *author* will be favoured during Information Gathering, and the term *reviewer* will be favoured during Information Inference.

4.1. Information Gathering

During Gathering, an information source such as a Conference Management System is used to extract the following:

Author Set

The author set $\mathcal{A}$ is an ordered set of n pairs $(a, name)$ where a is a natural number used for indexing, and "*name*" is the author's name.

$$\mathcal{A} = \{(a, name) \mid a \in \{1, 2, 3, \ldots, n\}, \textit{ and "name" is the name of the a-th author}\} \tag{1}$$

Paper Set

The Paper Set $\mathcal{P}$ is an ordered set of m pairs $(p, paper)$ where p is a natural number indexing the paper and "*paper*" is an identifier (e.g. the title) for the paper.

$$\mathcal{P} = \{(p, paper) \mid p \in \{1, 2, 3, \ldots, m\}, \textit{ and "paper" is an identifier for the p-th paper}\} \tag{2}$$

The keyword set $\mathcal{K}$ is an ordered set of k pairs $(w, keyword)$ where w is a natural number indexing the keyword, and "*keyword*" is the keyword.

$$\mathcal{K} = \{(w, keyword) \mid w \in \{1, 2, 3, \ldots, k\}, \textit{ and "keyword" is the w-th keyword}\} \tag{3}$$

Authorship Matrix

The Authorship Matrix $W \in \{0, 1\}^{m \times n}$ is a binary matrix such that:

$$W_{ij} = \begin{cases} 1 & \textit{if paper } i \textit{ is written by author } j \\ 0 & \textit{otherwise} \end{cases} \tag{4}$$

Keyword-Paper Matrix

The Keyword-Paper Matrix $P \in \{0, 1\}^{m \times k}$ is a binary matrix such that:

$$P_{ij} = \begin{cases} 1 & \textit{if paper } i \textit{ contains keyword } j \\ 0 & \textit{otherwise} \end{cases} \tag{5}$$

4.2. Information Inference

The information gathered in the previous step is used to infer the following matrices through the described calculations:

Keyword Expertise Matrix

The Keyword Expertise Matrix $K \in Z^{*\ k\times n}$ reflects the expertise of each reviewer on each keyword. The expertise is quantified as the number of papers that the reviewer has submitted with such keyword.

$$K_{ij} = \#\ \textit{of papers that reviewer } j \textit{ submitted with keyword } i \tag{6}$$

The Keyword Expertise Matrix can be calculated as:

$$K = P^T \cdot W \tag{7}$$

Expertise Matrix

The Expertise Matrix $E \in Z^{*\ m\times n}$ reflects the expertise of each reviewer the domain of each paper. Each element E_{ij} is the expertise of reviewer j on the keywords related to paper i.

$$E_{ij} = \ \#\ \textit{of instances that reviewer } j \textit{ has used keywords present in paper } i \tag{8}$$

The Expertise Matrix is calculated as:

$$E = P \cdot K = P \cdot P^T \cdot W \tag{9}$$

The matrix $P \cdot P^T$ can be understood as the correlation between papers in terms of keywords. It is a positive definite matrix where the element $[P \cdot P^T]_{ij}$ is the number of keywords present in both papers at the same time. Previous authors have also stated the opportunity to map relationships between reviewers and papers by an intermediate mapping of the relationships between the papers of the reviewers and the papers to review (see e.g. [12]).

Co-authorship Matrix

The co-authorship $\Phi \in Z^{*\ n\times n}$ is defined as:

$$\Phi_{ij} = \ k\ ,\ \textit{iff the i-th author submitted k papers with the j-th author} \tag{10}$$

The co-authorship matrix is calculated as:

$$\Phi = W^T \cdot W \tag{11}$$

The diagonal elements Φ_{ii} are the number of papers that the i-th author has submitted.

Veto Matrix

The Veto Matrix $V \in \{0,1\}^{m \times n}$ is a binary matrix which represents which reviewers are allowed to review which paper and reflects e.g. conflicts of interest.

$$V_{ij} = \begin{cases} 0 & \textit{if author } j \textit{ is not allowed to review paper } i \\ 1 & \textit{otherwise} \end{cases} \tag{12}$$

If $[W \cdot \Phi]_{ij} > 0$ then $V_{ij} = 0$ reflecting that authors have a conflict of interest when reviewing their own paper as well as any paper of their co-authors. If other conflicts of interest such as belonging to the same affiliation are identified, they can be also reflected in the veto matrix.

4.3. Optional pre-processing

Unqualified reviewers and isolated papers may be removed prior to the assignment.

Removing unqualified reviewers

Some reviewers may not have any expertise in any paper which they are allowed to review. They may be therefore removed before the assignment.

The k-th reviewer is unqualified for reviewing if and only if:

$$\sum_{i=1}^{m} [E \otimes V]_{i,k} = 0 \tag{13}$$

where $\otimes$ is the Schur product.

Removing isolated papers

We define isolated papers as those for which there is no available reviewer with any expertise and without a conflict of interest. Isolated papers may be removed before proceeding to the assignment.

The k-th paper is isolated if and only if:

$$\sum_{j=1}^{n} [E \otimes V]_{k,j} = 0 \tag{14}$$

5. Expertise Matching. Mathematical formulation.

The considered EM problem is to automatically assign one paper to each reviewer whilst considering their expertise and potential conflicts of interest. Additionally, it is sought to guarantee that all papers get similar number of reviewers.

Assume that the following are given:

- Reviewer set $\mathcal{A}$, and paper set $\mathcal{P}$ with m papers and n reviewers (see Equations 1 and 2).
- Expertise of the reviewers in the papers given by a cost matrix E, where E_{ij} is the expertise of reviewer j in paper i. The expertise matrix retrieved in Eq. 9 can be used for this purpose, or any other expertise matrix existing in literature.
- Veto matrix V (see Eq. 12).

The goals are:

- Assign one paper to each reviewer.
- Balance the assignment in such way that all papers get a similar number of reviewers. This is done by assign to every paper a minimum number of reviewers equal to $floor(n/m)$ and a maximum number of reviewers equal to $ceil(n/m)$.
- Maximize the total expertise of the reviewers in the assigned papers.
- Don't assign a paper to a vetoed author.

This can be resolved by calculating the assignment matrix A which maximizes the following optimization problem.

$$A = arg \max_{A_{ij} \in \{0,1\}} \sum_{i=1}^{m} \sum_{j=1}^{n} E_{ij} A_{ij} \tag{15}$$

$$\text{subject to } \sum_{i=1}^{m} A_{ij} = 1 \text{ for } j = 1, \cdots, n \tag{16}$$

$$\text{and } \sum_{j=1}^{n} A_{ij} \geq floor(n/m) \text{ for } i = 1, \cdots, m \tag{17}$$

$$\text{and } \sum_{j=1}^{n} A_{ij} \leq ceil(n/m) \text{ for } i = 1, \cdots, m \tag{18}$$

$$\text{where } Aij \begin{cases} = 0 & \text{if } V_{ij} = 0 \\ \in \{0, 1\} & \text{otherwise} \end{cases} \tag{19}$$

where A_{ij} is the resulting binary matrix which assigns reviewers to papers such that, if $A_{ij} = 1$ then the j-th reviewer is assigned to the i-th paper. Eq. 15 expresses that the assignment A is selected to maximize the total expertise of the reviewers in the assigned papers. Eq. 16 is a constrain which indicates that every reviewer is assigned precisely one paper. Equations 17 and 18 are constrains which express that every paper gets assigned at least $floor(n/m)$ reviewers and no more than $ceil(n/m)$ reviewers. Eq. 19 forces that papers are not assigned to vetoed reviewers.

Due to the nature of the feasibility set, the solution of this problem is of combinatorial nature. To grasp an idea on the computational complexity of this problem, assigning 1000 reviewers to 1000 papers leads to $1000! \simeq 4 \cdot 10^{102567}$ possible combinations. It is practically impossible to evaluate all the combinations and find the one which maximizes the cost function while satisfying the constrains. Some methods often used for integer programming are genetic algorithms and branch and bound methods. However, genetic algorithms often rely on the selection of a representative initial population of solutions which is hindered by the size of the feasibility set. The branch and bound methods depend on creating a tree which structures the candidates in the feasibility set. Another common approach to resolve such problems is to reformulate the initial problem in a shape which can be resolved efficiently, such as a convex problem. This often leads to approximations of the original problem. The following Sec. 6 will resolve this problem by decomposing it in unimodular problems which can be resolved efficiently without the need of approximations.

6. Convex Expertise Matching (EME)

This section introduces a Convex Expertise Matching (ConvEM) method to approximate and resolve any EM problem as the formulated in Eqs.15-19). ConvEM is based on decomposing the problem in separate convex sub-problems with unimodular properties by having equal number of reviewers and papers as in Equations 20-23.

$$A = arg \min_{A_{ij} \in \{0,1\}} \sum_{i=1}^{n} \sum_{j=1}^{n} C_{ij} A_{ij} \tag{20}$$

$$\text{subject to } \sum_{j=1}^{n} A_{ij} = 1 \text{ for } i = 1, \cdots, n \tag{21}$$

$$\text{and } \sum_{i=1}^{n} A_{ij} = 1 \text{ for } j = 1, \cdots, n \tag{22}$$

$$with\ C_{ij} = \begin{cases} -E_{ij} & if\ V_{ij} = 1 \\ +\infty & otherwise \end{cases} \tag{23}$$

where C is obtained from the negative of E to convert a maximization problem in a minimization problem, and where the cost to assign a paper to a vetoed reviewer is $+\infty$.

This AP is a special type of Linear Programming (LP), where the coefficient matrix associated to the equalities is totally unimodular. For this special case, the problem becomes a traditional continuous Linear Program, which can be solved efficiently (see [16]). The solution can be found e.g., using a Simplex algorithm (see [17]). Other methods such as the Stepping Stone, the Hungarian algorithm (see [18]), or the Push-Pull algorithm are often used (see [19]). Having a totally unimodular coefficient matrix means that the equalities can be dropped, and the problem becomes convex. Convex problems are known for being solved quickly and reliably up to a very large size of the problem. An assignment of 1000 reviewers to 1000 papers can be resolved in a few seconds with any of those algorithms using a modern computer.

We now propose a generic method for Convex Expertise Matching (ConvEM) which is based on decomposing the problem in separate convex sub-problems with totally unimodular coefficient matrix as the problem given in Equations 20-23.

Step 1: split the reviewer set $\mathcal{A}$ in $ceil(n/m)$ disjoint ordered sets (e.g.

randomly), such that:

$$\begin{aligned} \mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2 \cdots \cup \mathcal{A}_{ceil(n/m)} \\ \mathcal{A}_1 \cap \mathcal{A}_2 \cdots \cap \mathcal{A}_{ceil(n/m)} = \emptyset \\ |\mathcal{A}_i| = m, \forall i = 1, 2, ..., floor(n/m) \\ |\mathcal{A}_{ceil(n/m)}| = n - floor(n/m) \cdot m \end{aligned} \tag{24}$$

The reviewer sets $\mathcal{A}_i$ have as many reviewers as the total number of papers, except the last reviewer set $\mathcal{A}_{ceil(n/m)}$ which has the remaining $n - floor(n/m) \cdot m$ reviewers.

Step 2: For each of the reviewer sets $\mathcal{A}_i$, extract the Expertise Matrix $[E]_i$ and veto matrix $[V]_i$, which are formed by all the columns from E and V corresponding to the reviewers in $\mathcal{A}_i$.

Step 3 Augment the last reviewer set $\mathcal{A}_{ceil(n/m)}$ with $floor(n/m)$ "dummy" reviewers in order to have equal number of reviewers and papers. "Dummy" reviewers have no expertise neither any veto. The matrices $[E]_{ceil(n/m)}$ and $[V]_{ceil(n/m)}$ have to be augmented with $floor(n/m)$ columns of zeros.

Step 4 Resolve the resulting $ceil(n/m)$ convex APs with the shape in Equations 20-23.

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7. Baseline Greedy Assignment

This section introduces a greedy assignment method which will be used in Sec. 9 for performing a comparison with the introduced ConvEM.

Input. Reviewer Expertise Matrix E, Veto Matrix V.
Output. Assignment Matrix A.

Initialization
Step a**.** Set $A_{ij} = 0, \ \forall (i, j)$.
Step b**.** Set a cost of $-\infty$ for vetoes, i.e., if $V_{ij} = 0$ set $E_{ij} = -\infty$.

Start
Step 1**.** Choose E_{kl} as the largest value in C and assign the l-th reviewer to the k-th paper. The assignment is performed by setting $A_{kl} = 1$.

Step 2. Set all the values in the k-th row and in the l-th column of E to $-\infty$. That is, set $E_{il} = -\infty$, $\forall i = 1, 2, .., m$, and set $E_{kj} = -\infty$, $\forall j = 1, 2, .., n$.

Step 3. If $\min\limits_{(i,j)}(E_{ij}) > -\infty$, then return to Step 1.

End

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8. Quality Metrics for Reviewer Assignment Problems

The following quality metrics for RAP methods are introduced.

Total Review Expertise

The Total Review Expertise Q, is the function to maximize during RAP.

$$Q = \sum_{i=1}^{n} \sum_{j=1}^{n} E_{ij} A_{ij} \tag{25}$$

Average Reviewer Expertise

Dividing Q by the number of assigned reviews gives the Average Reviewer Expertise denoted by $\hat{Q}$.

$$\hat{Q} = \frac{\sum\limits_{i=1}^{n} \sum\limits_{j=1}^{n} E_{ij} A_{ij}}{||A||_0} \tag{26}$$

where $||.||_0$ denotes the 0-norm.

Number of reviewers without expertise

The number of times that a paper is assigned to a reviewer without relevant qualifications is denoted as $N_\emptyset$.

$$N_\emptyset = n - ||E \otimes A||_0 \tag{27}$$

9. Case Study

The conference program form the 2019 IEEE Conference on Decision and Control (CDC 2019) has been used for this case study. The conference program as well as the files to run this case study are distributed at [20].

The conference program includes an Author Index and a Keyword Index. The Author Index lists all the authors together with the identifier of their publications. The keyword Index lists all the individual keywords together with the identifier of the publications which include them. There is a total of 3043 authors and 1360 papers.

We will assign review tasks to each of the conference authors. We will therefore use the terms *author* and *reviewer* interchangeably.

The undertaken steps on IR have been:

1. Information Gathering:
    - Parsing and processing the Author Index to determine: the Author Set $\mathcal{A}$, the Paper Set $\mathcal{P}$, and the Authorship Matrix W.
    - Parsing and processing the Keyword Index to determine: the Keyword Set $\mathcal{K}$, and the Keyword-Paper Matrix P.
2. Information Inference by Calculating the Expertise Matrix (see Eq. 9) and Veto Matrix (see Eq. 12).
3. Pre-processing, where 30 reviewers have been identified as unqualified and removed from the Author Set. No isolated papers are present.

After IR, the number of reviewers is 3013, and the number of papers is 1360.

The output from IR is used to resolve four EM cases. These cases are selected because the introduced ConvEM is guaranteed to be optimal only for equal number of papers and reviewers. Table 1 summarizes, for each of the cases, the averaged performance indications from 100 runs of both ConvEM and the baseline.

Case 1. More reviewers than papers

The full dataset is used, with 3051 authors/reviewers and 1360 papers. Consequently, in ConvEM the problem is divided in $ceil(3051/1360) = 3$ individual APs. Each of the first and second APs include all the papers and a random subset of 1360 authors. The third AP includes the remaining

	Case 1		Case 2		Case 3		Case 4	
perf. $\downarrow$ \ **method** $\rightarrow$	Conv	Base	Conv	Base	Conv	Base	Conv	Base
$\sum_{i=1}^{100} Q_i$	8844	9052	3918	3695	7830	7547	1016	1007
$\max_{i=\{1,\ldots 100\}} Q_i$	8863	9077	3984	3764	7878	7594	1083	1069
$\min_{i=\{1,\ldots 100\}} Q_i$	8825	9027	3840	3627	7770	7491	963	954
$\sum_{i=1}^{100} \hat{Q}_i$	2.9	2.97	2.88	2.72	2.88	2.77	3.07	3.04
$\max_{i=\{1,\ldots 100\}} \hat{Q}_i$	2.9	2.98	2.93	2.77	2.9	2.79	3.27	3.23
$\min_{i=\{1,\ldots 100\}} \hat{Q}_i$	2.89	2.96	2.82	2.67	2.86	2.75	2.91	2.88
Average n^o of reviewers without expertise	0.7 (0%)	0 (0%)	0.25 (0%)	22.79 (1.7%)	0.75 (0%)	36.51 (1.3%)	0 (0%)	0 (0%)
Average n^o of papers with 0 reviewers	0 (0%)	29 (2.1%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1029 (75.7%)	1029 (75.7%)
Average n^o of papers with 1 reviewer	0 (0%)	192.86 (14.2%)	1360 (100%)	1360 (100%)	0 (0%)	0 (0%)	331 (24.3%)	331 (24.3%)
Average n^o of papers with 2 reviewers	1029 (75.7%)	556.28 (40.9%)	0 (0%)	0 (0%)	1360 (100%)	1360 (100%)	0 (0%)	0 (0%)
Average n^o of papers with 3 reviewers	331 (24.3%)	581.86 (42.8%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)

Table 1: Performance indicators for ConvEM (columns named Conv) and the greedy baseline (columns named *Base*) in the different cases of the case study.

authors and additional ”dummy” authors to convert the problem to totally unimodular as described in Sec. 6.

By looking in Table 1 at the average, minimum and maximum values of Q and $\hat{Q}$, it can be concluded that the initial randomization of the author sets has not shown a significant impact in the quality of the solution. Any of the 100 random runs has reached an acceptable solution. The split in APs implies that 1029 papers will receive 2 reviewers and 331 papers will receive 3 reviewers.

Comparing the solution given by ConvEM with the one achieved by the greedy baseline, it can be observed that ConvEM obtains a slightly better performance in terms of the average Q. However, the greedy baseline violates the constrains which require that all papers get a minimum of two reviewers. This leads to e.g. 24.54 papers with 0 reviewers and 207.28 papers with one reviewer in average.

Case 2. Same number of reviewers as papers

Subsets with all the 1360 papers and a random selection of 1360 authors are used.

The solutions reached by ConvEM are guaranteed to be optimal. The greedy baseline achieves values of Q and $\hat{Q}$ inferior to the optimal, but rather close. However, the greedy baseline assigns around 1.7% of authors with no expertise.

Case 3. The number of reviewers is a multiple of the number of papers

Subsets with all the 1360 papers and a random selection of 2720 authors are used.

Using ConvEM, the problem is split in two sub-problems with the same number of papers and reviewers (as in Case 2). The solution for each of the sub-problems is guaranteed to be optimal. All of the indicators for both ConvEM and the greedy baseline are similar than in Case 2.

Case 4. Less reviewers than papers

Subsets with all the 1360 papers and a random selection of 331 authors are used.

ConvEM guarantees optimal solution in this case due to the addition of "dummy" authors which do not contribute to the cost function and allow to formulate the problem as convex.

The solution given by the greedy baseline is inferior since it is not guaranteed to be optimal. It is however rather close to the optimal in this case study.

10. Potential Extensions of the introduced AI for RAP

This section discusses and demonstrates the flexibility and potential of the introduced AI by discussing possible extensions and integration of previous research.

Cost function changes

The IR step used in this paper retrieves an the expertise matrix relating papers and reviewers. Notice that in the RAP formulation (see Equations 15-19) the problem can be resolved with any other definition of similar expertise matrices introduced in literature, such as the ones obtained by: i) parsing abstracts of the papers to review and parsing abstracts from reviewers' homepages (see [11]) ii) processing free text by using Vector Space Models in [10] together with e.g. the Keyphrase Extraction Tool introduced in [21], iii) using the sentence pair modeling in [12] to calculate the distance between reviewers and papers by processing titles and abstracts with convolutional neural networks, iv) the use of authority, research interest and relevance in the cost function as introduced by [13].

Alternatively, the expertise matrix can be substituted by e.g. a bidding matrix generated by allowing reviewers to bid on the papers that they want to review (see [6]).

Multiple papers to each reviewer

The introduced ConvEM can also be used to assign multiple papers for each reviewer. This can be done by applying ConvEM sequentially as many times as the chosen number of papers that each reviewer will get assigned. Between sequential applications of ConvEM, the Veto matrix has to be updated such that if author j has been assigned to review paper i, then $V_{ij} = 0$. This update of the Veto matrix prevents that the same paper is again assigned to the same author in subsequent applications of ConvEM. As demonstration of the possible extensions, the appendix includes extracts from the solutions to the case study when assigning 2 and 3 papers to each reviewer.

It is part of future research to investigate hot to integrate reviewer quotas and paper quotas, which are used to state the maximum number of papers that individual reviewers should be assigned and the maximum number of reviewers that individual papers should be assigned to. The use of these quotas leads to more generalized Reviewer Assignment Problems, which have previously been posed in the literature (see e.g. [13, 9, 14]).

Assignment to different reviewer pools

This paper focuses on a pool of reviewers formed by the conference's authors, due to the availability of extracting information of the expertise of the reviewers from their own publications. Using other information retrieval methods, it would be possible to resolve the assignment problem for pools of reviewers composed by experts which are not necessarily authors in the conference. For example, PC members could state their own expertise by choosing from a list of keywords.

11. Conclusions

Reviewer Assignment Problems (RAP) are often addressed in two steps. The first step is Information Retrieval, where the expertise of the reviewers in the domain of the papers is retrieved. The second step is Expertise Matching (EM), where reviewers are assigned to papers in order to maximize a cost function with constrains.

In the literature review, it was found that, EM is widely performed through the use of combinatorial search with Mixed Integer Programming problems, where the number of possible solutions for matching n papers to n authors is $n!$. This means e.g. that there are more than 3 million combinations for matching 10 reviewers to 10. These methods have been applied only to very small sets of papers and reviewers. Other methods for application on larger datasets exist on literature, but depend upon complicated reformulations and often involve inadequate approximations for the convexification of the problem.

A main contribution to this paper is on the convex formulation of EM as a set of continuous Linear Programs which can be efficiently solved. This results in a method that we call Convex Expertise Matching (ConvEM). A simpler greedy algorithm for ConvEM has also been created in order to act as a baseline for comparison. ConvEM has achieved better performance than the baseline in all the presented cases.

EEM has been demonstrated in a dataset with more than 3000 reviewers and more than 1000 papers. During the literature review, no precedent has been found for resolving RAP in such large problems. Due to this new formulation, such assignment only takes a few seconds in a modern computer.

This paper also introduces an keyword-based information retrieval method to extract the expertise of the authors of a conference.

Potential extensions of ConvEM have been proposed in order to leverage other results in literature. It has been briefly demonstrated that ConvEM can also be used to resolve more generic assignments with reviewer quota. Two solutions are given in the appendix for: i) a quota of 2 papers for each reviewer, ii) a quota of 3 papers for each reviewer. It is the matter of future research to extend more explicitly the ConvEM for assignment with individual quotas for each reviewer and each paper as well as to evaluate its performance.

The concluding remarks are that:

- The introduced Artificial Intelligence for the Reviewer Assignment Problem has succeeded in accurately resolving large scale problems where the previous literature has failed.

- The introduced Artificial Intelligence has a large flexibility to be adapted in order to leverage existing methods for e.g. information retrieval or to resolve more generic assignments with reviewer and paper quotas.

Appendix A. Appendix. Examples of Assignment Solutions

This appendix includes extracts from solutions to the complete assignment in the case study in Sec. 9 where 1360 papers are assigned to 3051 reviewers.

Authors are listed with their related keywords. If there is a number in parenthesis after a keyword, it indicates the number of papers that the author has submitted using that keyword (if there is no number, it means just 1). After each author, the assigned paper(s) is/are listed with the keywords related to each paper.

Solution assigning 1 paper to each author

This is an extract from the solution to the case 1 in Sec. 9.
Author ID: Mager, Fabian, Author Keywords: Communication networks, Distributed control, Networked control systems
Paper ID: FrB21.2; Paper keywords: Communication networks, Distributed control, Networked control systems

Author ID: Maggio, Martina, Author Keywords: Fault detection, Fault tolerant systems, Information theory and control
Paper ID: WeC21.6; Paper keywords: Game theory, Information theory and control, Sensor networks

Author ID: Maggiore, Manfredi, Author Keywords: Algebraic/geometric methods, Constrained control, Robotics
Paper ID: WeC07.4; Paper keywords: Constrained control, Optimal control, Robotics

Author ID: Maggistro, Rosario, Author Keywords: Delay systems, Mean field games, Network analysis and control, Optimal control(2), Systems biology
Paper ID: FrC23.5; Paper keywords: Large-scale systems, Network analysis and control, Optimal control

Author ID: MAGHENEM, Mohamed Adlene, Author Keywords: Control applications, Hybrid systems(2), Lyapunov methods(2), Observers for nonlinear systems, Output regulation
Paper ID: WeB14.1; Paper keywords: Aerospace, Hybrid systems, Lyapunov methods

Author ID: Magossi, Rafael, Author Keywords: Computational methods, Power electronics, Stability of linear systems
Paper ID: FrC17.5; Paper keywords: Power electronics, Smart grid, Stability

of linear systems

Author ID: Mahajan, Aditya, Author Keywords: Large-scale systems, Learning, Markov processes, Network analysis and control, Networked control systems, Stochastic optimal control(2), Stochastic systems(2)
Paper ID: FrC19.5; Paper keywords: Large-scale systems, Stochastic optimal control, Stochastic systems

Author ID: Majumdar, Rupak, Author Keywords: Formal Verification/Synthesis, Robust adaptive control, Uncertain systems
Paper ID: ThB14.3; Paper keywords: Nonlinear output feedback, Robust adaptive control, Uncertain systems

Author ID: Malabre, Michel, Author Keywords: Communication networks, Linear systems, Robotics
Paper ID: ThB07.2; Paper keywords: Networked control systems, Robotics

Author ID: Malan, Albertus Johannes, Author Keywords: Decentralized control, Energy systems, Stability of nonlinear systems
Paper ID: ThC05.1; Paper keywords: Energy systems, Stability of nonlinear systems

Author ID: Maley, Carlo, Author Keywords: Biomolecular systems, Pattern recognition and classification, Systems biology
Paper ID: FrC01.3; Paper keywords: Systems biology

Solution assigning 2 papers to each author

This is an extraction from the solution using the extension to assign 2 papers to each reviewer, as discussed in Sec. 10.
Author ID: Mager, Fabian, Author Keywords: Communication networks, Distributed control, Networked control systems
Paper ID: FrB21.2; Paper keywords: Communication networks, Distributed control, Networked control systems
Paper ID: ThB12.1; Paper keywords: Communication networks, Control over communications, Networked control systems

Author ID: Maggio, Martina, Author Keywords: Fault detection, Fault tolerant systems, Information theory and control
Paper ID: FrB01.2; Paper keywords: Biomolecular systems, Information theory and control, Stochastic systems
Paper ID: ThC18.5; Paper keywords: Fault detection, Fault tolerant systems, Linear systems

Author ID: Maggiore, Manfredi, Author Keywords: Algebraic/geometric methods, Constrained control, Robotics
Paper ID: WeB15.2; Paper keywords: Algebraic/geometric methods, Constrained control, Optimal control
Paper ID: FrA02.5; Paper keywords: Algebraic/geometric methods, Constrained control, Linear systems

Author ID: Maggistro, Rosario, Author Keywords: Delay systems, Mean field games, Network analysis and control, Optimal control(2), Systems biology
Paper ID: FrC23.5; Paper keywords: Large-scale systems, Network analysis and control, Optimal control
Paper ID: WeA09.5; Paper keywords: Game theory, Mean field games, Optimal control

Author ID: MAGHENEM, Mohamed Adlene, Author Keywords: Control applications, Hybrid systems(2), Lyapunov methods(2), Observers for nonlinear systems, Output regulation
Paper ID: FrC13.3; Paper keywords: Hybrid systems, Linear systems, Output regulation
Paper ID: WeB14.1; Paper keywords: Aerospace, Hybrid systems, Lyapunov methods

Author ID: Magossi, Rafael, Author Keywords: Computational methods, Power electronics, Stability of linear systems
Paper ID: FrC17.5; Paper keywords: Power electronics, Smart grid, Stability of linear systems
Paper ID: ThA01.4; Paper keywords: Computational methods, Genetic regulatory systems, Hybrid systems

Author ID: Mahajan, Aditya, Author Keywords: Large-scale systems, Learning, Markov processes, Network analysis and control, Networked control sys-

tems, Stochastic optimal control(2), Stochastic systems(2)
Paper ID: FrC19.5; Paper keywords: Large-scale systems, Stochastic optimal control, Stochastic systems
Paper ID: FrA19.4; Paper keywords: Learning, Stochastic optimal control, Stochastic systems

Author ID: Majumdar, Rupak, Author Keywords: Formal Verification/Synthesis, Robust adaptive control, Uncertain systems
Paper ID: ThB21.2; Paper keywords: Filtering, Networked control systems, Uncertain systems
Paper ID: ThB14.3; Paper keywords: Nonlinear output feedback, Robust adaptive control, Uncertain systems

Author ID: Malabre, Michel, Author Keywords: Communication networks, Linear systems, Robotics
Paper ID: FrA02.5; Paper keywords: Algebraic/geometric methods, Constrained control, Linear systems
Paper ID: WeA05.2; Paper keywords: Embedded systems, Linear systems, Predictive control for linear systems

Solution assigning 3 papers to each author

This is an extraction from the solution using the extension to assign 3 papers to each reviewer, as discussed in Sec. 10.
Author ID: Mager, Fabian, Author Keywords: Communication networks, Distributed control, Networked control systems
Paper ID: FrB21.2; Paper keywords: Communication networks, Distributed control, Networked control systems
Paper ID: WeB05.4; Paper keywords: Distributed control, Networked control systems, Switched systems
Paper ID: FrC21.1; Paper keywords: Adaptive control, Distributed control, Networked control systems

Author ID: Maggio, Martina, Author Keywords: Fault detection, Fault tolerant systems, Information theory and control
Paper ID: FrA13.5; Paper keywords: Information technology systems, Information theory and control, Uncertain systems
Paper ID: WeC03.4; Paper keywords: Adaptive control, Fault detection,

Time-varying systems
Paper ID: ThC18.5; Paper keywords: Fault detection, Fault tolerant systems, Linear systems

Author ID: Maggiore, Manfredi, Author Keywords: Algebraic/geometric methods, Constrained control, Robotics
Paper ID: WeC07.4; Paper keywords: Constrained control, Optimal control, Robotics
Paper ID: WeB15.2; Paper keywords: Algebraic/geometric methods, Constrained control, Optimal control
Paper ID: FrB24.3; Paper keywords: Constrained control, Iterative learning control, Robotics

Author ID: Maggistro, Rosario, Author Keywords: Delay systems, Mean field games, Network analysis and control, Optimal control(2), Systems biology
Paper ID: FrC23.5; Paper keywords: Large-scale systems, Network analysis and control, Optimal control
Paper ID: WeA09.5; Paper keywords: Game theory, Mean field games, Optimal control
Paper ID: ThC14.6; Paper keywords: Optimal control

Author ID: MAGHENEM, Mohamed Adlene, Author Keywords: Control applications, Hybrid systems(2), Lyapunov methods(2), Observers for nonlinear systems, Output regulation
Paper ID: WeB14.1; Paper keywords: Aerospace, Hybrid systems, Lyapunov methods
Paper ID: FrC13.3; Paper keywords: Hybrid systems, Linear systems, Output regulation
Paper ID: FrC22.1; Paper keywords: Control applications, Lyapunov methods, Maritime control

Author ID: Magossi, Rafael, Author Keywords: Computational methods, Power electronics, Stability of linear systems
Paper ID: FrC17.5; Paper keywords: Power electronics, Smart grid, Stability of linear systems
Paper ID: WeC05.4; Paper keywords: Computational methods, Constrained control
Paper ID: FrC06.6; Paper keywords: Computational methods, Energy sys-

tems, Modeling

Author ID: Mahajan, Aditya, Author Keywords: Large-scale systems, Learning, Markov processes, Network analysis and control, Networked control systems, Stochastic optimal control(2), Stochastic systems(2)
Paper ID: FrC19.5; Paper keywords: Large-scale systems, Stochastic optimal control, Stochastic systems
Paper ID: FrA19.4; Paper keywords: Learning, Stochastic optimal control, Stochastic systems
Paper ID: FrA21.5; Paper keywords: Networked control systems, Stochastic optimal control, Stochastic systems

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