Graphical Abstract

Automatic assignment of reviewers in peer reviewed conferences

Miguel Castaño Arranz

Highlights

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Automatic assignment of reviewers in peer reviewed conferences

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Abstract

This paper introduces an Artificial Intelligence (AI) for the Reviewer Assignment Problem (RAP). The considered RAP is to assign a review task to each of the authors of a conference. An AI for RAP consists of a Information Retrieval step and an Expertise Matching step. The main contribution of this paper is in casting a novel Convex Expertise Matching (CEM) scheme for large scale assignments. CEM 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 case study for a conference with 3051 authors and 1360 papers. In order to investigate the performance of CEM, a Greedy Expertise Matching (GEM) scheme is introduced and used as baseline. Finally, this paper discusses the large potential to adapt CEM to e.g. i) deal with more generic RAP problems with author quotas 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 focus of this paper. This is done by maximizing the quantified expertise of the reviewers assigned to the manuscripts.

According to the study on computer science papers performed 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 stage 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 assigned papers to the reviewers 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 assigns review assignments to 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 particular domain of each paper, as well as their conflicts of interest. This information will be later used in the EM to run an optimization scheme in order to assign review assignments to each of the authors.

An important contribution of this paper is the introduction of a new method for EM, which is formulated as an optimization problem. The method is hereby named Efficient Expertise Matching (EEM).

The mathematical formulation of EEM is similar than 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 can be efficiently solved without the need of any approximations.

The introduced EEM has been illustrated in a large scale dataset with 3051 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, and datasets of up to 338 papers have only 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 has also been 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 Efficient EM (EEM).

Compatible IR methods need to provide with the required information for performing EEF, i.e. with a quantification of the expertise of reviewers in papers and with conflicts of interest. Compatible work on IR in [6] consists of parsing abstracts in search of keywords using the Porter stemming algorithm introduced in [10]. Compatible IR methods evaluated in [11] use the Vector Space Model (see [12]). Compatible IR methods in [13] require that reviewers provide with a personal web page with their professional interests.

Most of the papers which focus on IR, include also an EM method for illustration. For the papers on IR which are cite above (see [6, 11, 13]), the EM method 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 [14]).

The Efficient 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 [14]). This review of previous work will therefore focus on EM methods for ARAP.

Some EM methods such as the introduced by Karimzadehgan et al. in [9] formulate the EM as an optimization problem. Karimzadehgan et al. resolve the optimization problem in 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 far from optimal. 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. Each reviewer has a maximum quota of papers to be assigned, but some reviewers may reach the quota and some may receive no paper.

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 [15]).

The application of EM to larger datasets is facilitated by the convexification of the optimization problem. The EM method introduced by Wahid et al. in [16] can be applied to larger sets of papers and reviewers due to the fact that the problem has been convexified as a minimum convex-cost network flow problem (see [17]). However, such convexifications often result in approximations or reformulations which do not actually resolve the real problem. In [16], 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 in practice. The EM method introduced by Wahid et al. only assigns papers to reviewers when a value of 1 is obtained, but then the effective value of the cost function for such assignment will differ from the calculated as optimal. The algorithm has been tried on a medium size conference of 338 papers and 354 reviewers.

Other EM methods such as the introduced in [18] are based on logic rules and assign papers to reviewers one by one. These EM methods provide assignments which are far from optimality, but they can however be applied to larger datasets than those methods based on combinatorial solutions.

3. Overview

This section provides an overview to the introduced AI for RAP as well as an outline of the sequel of the paper.

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 1. However, the main innovation is in EM. The innovation consists of splitting EM in efficient sub-problems. For a complete demonstration of of this innovation in EM, the following has been introduced (see numbered boxes in 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.

During Information Gathering (see 4.1), information is gathered e.g. from the conference management system to obtain the following:

- sets of papers, set of a authors and set of keywords,
- a binary matrix expressing authorship as a relationship between the set of authors and the set of papers,
- a binary matrix expressing the presence of keywords in papers as a relationship between the set of keywords and set of papers.

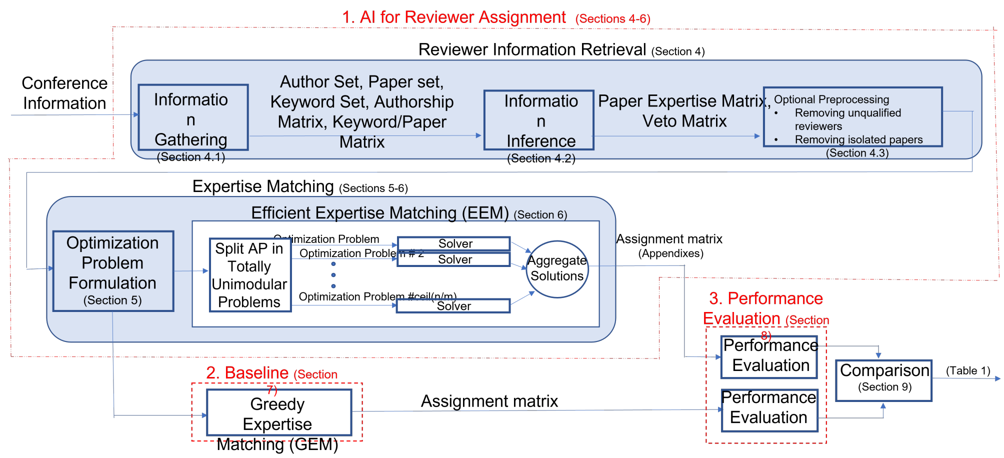

Figure 1:

During the Information Inference described in 4.2, the gathered information is transformed to the shape which is required as input for EM.

Additional pre-processing as described in Section 4.3 may be of interest prior to EM.

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) efficient solution to the EM optimization problem (see 6).

During the mathematical formulation of EM in 5, the problem is described as a cost function and a set of constraints. The cost function aims at maximizing the expertise of the reviewers in the papers that they are assigned. The constraints limit the number of papers assigned to each reviewer, limit the number of reviewers assigned to each paper, and specify conflicts of interest of reviewers in papers. The mathematical formulation leads to a large-scale combinatorial problem.

The main novelty of this paper is in formulating a computationally efficient solution named EEM, which is done in Section 6. EEM depends upon splitting the main optimization problem in totally unimodular sub-problems. Each of the totally unomodular sub-problems can be resolved with a variety of efficient solvers such as the Hungarian algorithm. The individual solutions to each totally unimodular sub-problems are then aggregated.

EEM is optimal only if the conditions for being totally unimodular are satisfied by the complete optimization problem. Otherwise, optimallity is only guaranteed for each of the sub-assignments in which the problem is decomposed. However, aggregating the solutions of the sub-assignments 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 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 favored during Information Gathering, and the term *reviewer* will be favored during Information Inference.

4.1. Information Gathering

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

- Set of authors, set of papers and set of keywords
- An authorship matrix describing who is author of which paper.
- A Keyword-Paper matrix describing which keywords are included in each paper.

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. [14]).

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-authorsip 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 an author has a conflict of interest when reviewing his/her own paper as well as any paper of 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 [1] whilst considering their expertise and potential conflicts of interest. Additionally, it is sought to guarantee that all papers get similar number of reviewers.

We formulate the problem of assigning one paper to each reviewer as follows [2].

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.

[1] This section assumes that information retrieval from a pool of reviewers has previously been performed. An option is using the method for information retrieval introduced in Sec. 4 where authors of conference papers become reviewers. We will therefore use only the term "*reviewers*" in this section. If the information retrieval method from Sec. 4 is used, then the reviewer set becomes equal to the author/reviewer set $\mathcal{A}$ in Eq. 1. The reviewer set will be in this section denoted as $\mathcal{A}$ for the sake of continuity.

[2] An extension for the assignment of multiple papers to each reviewer will be discussed later in Section 10

This can be resolved by calculating the assignment matrix A which minimizes 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. **??** will resolve this problem by decomposing it in unimodular problems which can be resolved efficiently without the need of approximations.

6. Efficient Expertise Matching (EME)

This section introduces an Efficient Expertise Matching (EEM) methodto approximate and resolve any EM problem as the formulated in Eqs.15-19). EEM is based on decomposing the problem in separate convex sub-problems with unimudular properties as in Equations 20-23.

The optimization problem described in in Eqs.15-19) can be rewritten as a classic Assignment Problem (AP) if there is an equal number of papers and reviewers (m=n). The problem would be formulated as:

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

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

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

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

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 [19]). The solution can be found e.g. using a Simplex algorithm (see [20]). Other methods such as the Stepping Stone, the Hungarian algorithm (see [21]), or the Push-Pull algorithm are often used (see [22]). Having a totally unimodular coefficient matrix means that the equalities can be dropped and the problem becomes convex (see "The assignment problem and totally unimodular matrices"). 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 Efficient Expertise Matching (EEM) 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:

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

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

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

Step 3 Augment the last reviewer set $\mathcal{A}_{ceil(n/m)}$ with as many "dummy" reviewers as needed in order to have equal number of reviewers and papers. "Dummy" reviewers have no expertise neither any veto. The matrix $[E]_{ceil(n/m)}$ has to be augmented with as many columns of zeros as the number of "dummy" reviewers. "Dummy" reviewers are added to square the AP. Dummy reviewers can be assigned to any paper and do not contribute to the cost function. An assignment of a "dummy" reviewers to a paper will simply be ignored and is not translated into any real-life action.

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 for searching a solution for the assignment problem in (see Equations 15-19). The greedy assignment will be used in Sec. **??** for performing a comparison with the introduced EEM.

A Greedy Assignment to locally optimize individual assignments at each stage is formulated as:

Input. Reviewer Expertise Matrix E, Veto Matrix V.

Output. Assignment Matrix A, such that $A_{ij} = 1$ if the j-th reviewer is assigned to the i-th paper, oherwise $A_{ij} = 0$. h

Initialization

Step a**.** Set $A_{ij} = 0, \ \forall (i, j)$.

Step b**.** Set a cost of $-\infty$ for vetoes. That is, if $V_{ij} = 0$, then set $E_{ij} = 0$.

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 are introduced for evaluation of RAP methods.

Total Review Expertise

The Total Review Expertise Q is hereby defined as:

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

Q is the total aggregated expertise, which is the function to maximize during RAP (see **??**).

Average Reviewer Expertise

Dividing the Total Review Expertise Q by the number of assigned reviews gives the average expertise of the reviewers, We will denote the Average Reviewer Expertise by $\hat{Q}$.

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

where $||.||_0$ denotes the 0-norm, or the number of elements in a matrix which are different from 0.

Number of reviewers without expertise

The number of times that a paper is assigned to a reviewer who doesn't have any expertise is denoted as $N_\emptyset$, and is calculated as:

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

9. Case Study

The conference program form the 2019 IEEE Conference on Decision and Control (CDC 2019) has been used as case study.

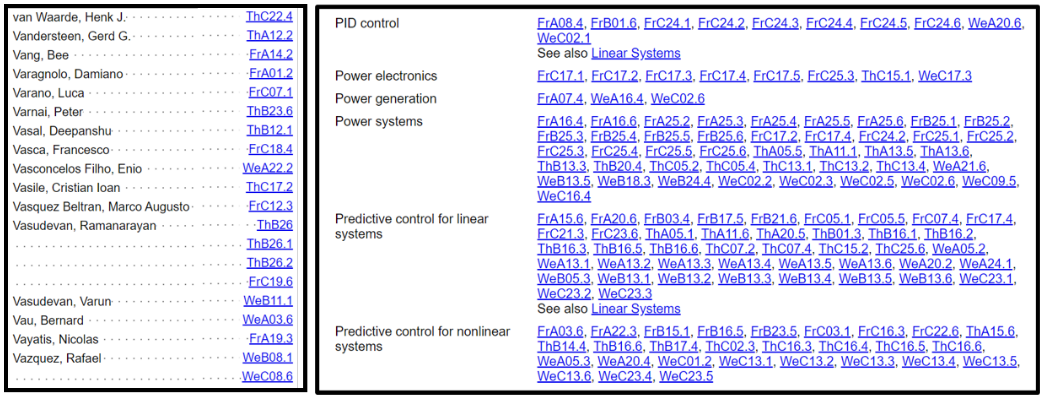
The conference program as well as the files to run this case study are distributed at [23].

The used data from the conference program consists of an Author Index and a Keyword Index. The Author Index lists all the authors together with the identifier of their publications. A sample of the Author Index is depicted in Fig. 2 (left). The keyword Index lists all the individual keywords together with the identifier of the publications which include them. A sample of the Author Index is depicted in Fig. 2 (right). There is a total of 3043 authors and 1360 papers.

In this case study 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, for determining the following: the Author Set $\mathcal{A}$, the Paper Set $\mathcal{P}$, and the Authorship Matrix W.
    - Parsing and processing the Keyword Index to determine the following: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.



van Waarde, Henk J.	ThC22.4
Vandersteen, Gerd G.	ThA12.2
Vang, Bee	FrA14.2
Varagnolo, Damiano	FrA01.2
Varano, Luca	FrC07.1
Varnai, Peter	ThB23.6
Vasal, Deepanshu	ThB12.1
Vasca, Francesco	FrC18.4
Vasconcelos Filho, Enio	WeA22.2
Vasile, Cristian Ioan	ThC17.2
Vasquez Beltran, Marco Augusto	FrC12.3
Vasudevan, Ramanarayan	ThB26
	ThB26.1
	ThB26.2
	FrC19.6
Vasudevan, Varun	WeB11.1
Vau, Bernard	WeA03.6
Vayatis, Nicolas	FrA19.3
Vazquez, Rafael	WeB08.1
	WeC08.6

PID control	FrA08.4, FrB01.6, FrC24.1, FrC24.2, FrC24.3, FrC24.4, FrC24.5, FrC24.6, WeA20.6, WeC02.1 See also Linear Systems
Power electronics	FrC17.1, FrC17.2, FrC17.3, FrC17.4, FrC17.5, FrC25.3, ThC15.1, WeC17.3
Power generation	FrA07.4, WeA16.4, WeC02.6
Power systems	FrA16.4, FrA16.6, FrA25.2, FrA25.3, FrA25.4, FrA25.5, FrA25.6, FrB25.1, FrB25.2, FrB25.3, FrB25.4, FrB25.5, FrB25.6, FrC17.2, FrC17.4, FrC24.2, FrC25.1, FrC25.2, FrC25.3, FrC25.4, FrC25.5, FrC25.6, ThA05.5, ThA11.1, ThA13.5, ThA13.6, ThB13.3, ThB20.4, ThC05.2, ThC05.4, ThC13.1, ThC13.2, ThC13.4, WeA21.6, WeB13.5, WeB18.3, WeB24.4, WeC02.2, WeC02.3, WeC02.5, WeC02.6, WeC09.5, WeC16.4
Predictive control for linear systems	FrA15.6, FrA20.6, FrB03.4, FrB17.5, FrB21.6, FrC05.1, FrC05.5, FrC07.4, FrC17.4, FrC21.3, FrC23.6, ThA05.1, ThA11.6, ThA20.5, ThB01.3, ThB16.1, ThB16.2, ThB16.3, ThB16.5, ThB16.6, ThC07.2, ThC07.4, ThC15.2, ThC25.6, WeA05.2, WeA13.1, WeA13.2, WeA13.3, WeA13.4, WeA13.5, WeA13.6, WeA20.2, WeA24.1, WeB05.3, WeB13.1, WeB13.2, WeB13.3, WeB13.4, WeB13.5, WeB13.6, WeC23.1, WeC23.2, WeC23.3 See also Linear Systems
Predictive control for nonlinear systems	FrA03.6, FrA22.3, FrB15.1, FrB16.5, FrB23.5, FrC03.1, FrC16.3, FrC22.6, ThA15.6, ThB14.4, ThB16.6, ThB17.4, ThC02.3, ThC16.3, ThC16.4, ThC16.5, ThC16.6, WeA05.3, WeA20.4, WeC01.2, WeC13.1, WeC13.2, WeC13.3, WeC13.4, WeC13.5, WeC13.6, WeC23.4, WeC23.5

Figure 2: Sample of the Author Index of CDC2019 (left). Sample of the Keyword Index of CDC2019.

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

In the reminding of this case study, we use the output from IR to resolve four Expertise Matching cases. These cases are selected because the introduced EEM is guaranteed to be optimal only for equal number of papers and reviewers. The baseline greedy assignment is used to establish comparisons with all the cases:

- Case 1. More reviewers than papers. Using the full Author Set and Paper Set with more reviewers than papers.
- Case 2 Equal number of reviewers and papers. Using random subsets of 1360 reviewers.
- Case 3 The number of reviewers is a multiple of the number of papers.
- Case 4 Less reviewers than papers.

Table 1 summarizes, for each of the cases, the averaged performance indications from 100 runs of both EEM and the baseline.

Case 1. More reviewers than papers

The full dataset is used, with 3051 authors/reviewers and 1360 papers. Consequently, in EEM 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 authors

	Case 1		Case 2		Case 3		Case 4	
perf. $\downarrow$ \ **method** $\rightarrow$	EEM	Baseline	EEM	Baseline	EEM	Baseline	EEM	Baselina
$\sum_{i=1}^{100} Q_i$	8844	9052	3918	3695	7830	7547	1016	1007
$\max_{i=\{1,\dots 100\}} Q_i$	8863	9077	3984	3764	7878	7594	1083	1069
$\min_{i=\{1,\dots 100\}} Q_i$	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
$\max_{i=\{1,\dots 100\}} \hat{Q}_i$	2.9	2.98	2.93	2.77	2.9	2.79	3.27	3.23
$\min_{i=\{1,\dots 100\}} \hat{Q}_i$	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 EEM and the greedy baseline in the different cases of the case study.

and additional "dummy" authors to square the problem as described in Sec. **??**.

In 100 randomized runs, the solutions from OPERAP-CES reached an average value of $Q = 6.7486$, $\hat{Q} = 2.184$. The maximum values are $Q = 6777$, $\hat{Q} = 2.1960$. The minimum values are $Q = 6635$, $\hat{Q} = 2.1747$. Therefore, in this case study 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 actually reached an acceptable solution. The split in APs implies that 1029 papers will received 2 reviewers and 331 papers will receive 3 reviewers.

Comparing the solution given by EEM with the one achieved by the greedy baseline, it can be observed that EEM 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.

In 100 randomized runs, the solutions reached by EEM have average values of $Q = 3918$ and $\hat{Q} = 2.88$. The maximum values are $Q = 3984$, $\hat{Q} = 2.93$. The minimum values are $Q = 3840$, $\hat{Q} = 2.82$. The solutions are guaranteed to be optimal.

The greedy baseline gives in comparison average values of $\hat{Q} = 2.93$ inferior to the optimal but rather close. However, the greedy algorithm 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 EEM, 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. In 100 randomized runs, the average value of Q_hat has been $\hat{Q} = 2.88$.

All of the indicators for both EEM and the 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.

EEM 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 includes discusses possible extensions of the introduced AI for RAP. These extensions include the integration of previous research. This section discusses and demonstrates the flexibility and potential of the introduced AI.

Cost function changes

In the IR step (see 4) we have retrieved the expertise metric relating papers and reviewers/authors by using the keywords of the submitted papers. Notice that in the RAP formulation (see Equations 15-**??**) the problem can be resolved with any other definition of similar expertise metrics introduced in literature, such as: i) the expertise metric obtained in [13] by parsing abstracts from the conference and abstracts from the publications in the reviewers' homepages ii) the paper-reviewer relevance obtained in [11] using Vector Space Models (VSM) together with e.g. the Keyphrase Extraction Tool (see KEA introduced in [24]) on free-text, iii) the sentence pair modeling used in [14] to calculate the distance between reviewers and papers processing titles and abstracts with convolutional neural networks, iv) the use of authority, research interest and relevance in the cost function as introduced by [15].

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 EEM can also be used to assign multiple papers for each reviewer. This can be done by applying EEM sequentially as many times as the chosen number of papers that each reviewer will get assigned. Between sequential applications of EEM, 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 EEM. 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. [15, 9, 16]).

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: a first step of information retrieval where the expertise of the reviewers in the domain of the papers is retrieved, and a second step of expertise matching where reviewers are assigned to papers in order to maximize a cost function based on the expertise and subject to constrains such as the number of papers assigned to reviewers.

In the literature review it was found that the expertise matching in the RAP is still performed widely through the use of Mixed Integer Programming techniques, 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 papers and therefore 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 involve inadequate approximations for the convexification of the problem.

A main contribution to this paper is on the formulation of the expertise matching problem as a continuous Linear Program which can be efficiently solved. Such formulation requires that: i) the number of papers and reviewers has to be the same, ii) one and only one paper is assigned to each reviewer, iii) each paper gets assigned one and only one reviewer.

The next main contribution of these paper is on using the formulation as continous LP to split problems of any size into a set of sub-problems which can be efficiently resolved. This results in a method that we call Efficient Expertise Matching (EEM). A simpler greedy algorithm for Expertise Matching has also been created in order to act as a baseline for comparison. EEM 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.

Whilst the main results are considered to be on introducing EEM, this paper also introduces an keyword-based information retrieval method to extract the expertise of the authors of a conference. However EEM can still be used with any other information retrieval step which results in a cost matrix for assigning papers to reviewers.

Potential extensions of EEM have been proposed in order to leverage other results in literature. It has been briefly demonstrated that EEM 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 EEM 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.

Early work in resolving RAP as Transportation Problems (TPs) was introduced in [25], and consisted in formulating Maximum Weight Capacitated Transshipment Problems (MWCTPs). The implementation in a case with 182 reviewers and 174 papers required significant manual work together with resolving 31,668 TPs in addition to the iterative resolution of MWCTPs until the solution with the largest possible threshold on the reviewer's expertise is found. Additionally, it is unclear which method been used to resolve the MWCTPs in order to obtain integer solutions. There is a wide range of methods for resolving TPs, but the optimal solution is not integer, unless the problem satisfies very specific conditions (such as total unimodulairity). Seeking integer solutions require methods which are more computationally expensive methods such as .... or combinatorial methods.....

Transportation Problems have been introduced in [26].

Greedy algorithms for assignment of review tasks have been used in [27] (for reviewing proposals).

A performance metric to compare assignment has been introduced in [27] (for reviewing proposals). It is called Sum of Residual Term Weight (SRTW) and aggregates the distance of the reviewers' expertise from a target expertise for each individual task.

The Hungarian algorithm (also known as Munkres algortihm) has been extended for nonrectangular matrices in [28].

The paper by Munkres is [29].

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 reg-

ulatory systems, Hybrid 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
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 systems, 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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