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Minimal-envy Conference Paper Assignment: Formulation and a Fast Iterative Algorithm

*Mao Tan
Hunan National Center for Applied Mathematics
Xiangtan University
Xiangtan, China
mr.tanmao@gmail.com

Zhuocen Dai
School of Computer Science
Xiangtan University
Xiangtan, China
zhuocend@protonmail.ch

Yuling Ren
School of Computer Science
Xiangtan University
Xiangtan, China
rmmnic@163.com;

Toby Walsh
School of Computer Science and Engineering,
University of New South Wales
Sydney, Australia
tw@cse.unsw.edu.au

Martin Aleksandrov
Institute of Software Engineering and Theoretical Computer Science
Technical University Berlin
Berlin, Germany
martin.aleksandrov@tu-berlin.de

***Abstract*—In conference review management, it is very common that many papers being assigned are not liked by some reviewers due to their specialties or personal interests. In this paper, we consider a reviewer might only envy other reviewers who get a better set of papers than his. In this context, we proposes a new bi-objective optimization assignment model to efficiently and fairly assign papers to many competing reviewers, in which an index that measures the amount of envy is introduced. A fast iterative algorithm is proposed to solve the problem. The experimental results on real datasets shows that the algorithm achieves efficient and fair results and good computing performance, especially on large scale problems. This work is also meaningful for a number of similar allocation or matching problems.**

***Index Terms*—Conference paper assignment problem, multi-objective optimization, Envy-index.**

I. Introduction

In recent years, many academic conferences are facing tremendous pressure of receiving too many submissions, e.g., AAAI 2020 received 7737 full-paper submissions, NeurIPS 2020 received 9467 submissions, automated and optimal conference paper assignment in review procedure has been well-known as a difficult and attractive topic in academic conference management.

The conference paper assignment problem (CPAP) has gotten the attraction of researchers from academia and industry. Many years ago, in order to yield high-quality reviews and higher satisfaction of reviewers, [1] studied the maximum match problem between the referees' expertise and the paper topics. Considering the difficulty to optimally solve the large size problem, they proposed a combined greedy/evolutionary algorithm and achieved a high satisfaction of referees with the papers they have been assigned. [2] proposed a new criterion on how to assign research proposals to reviewers, ordinal ranking, but not the common criterion welfare, is evaluated in their assignment. [3] described a variant of a bipartite graph to study a conference assignment problem to maximize the overall affinity. [4] studied the problem of assigning papers to referees, they considered a number of criteria and aimed at achieving fairness among referees/papers in the optimization. The approximation algorithms for different criteria are proposed in the work. Building on this extensive academic research, some paper assignment systems have been incorporated into systems in recent years, e.g., the Toronto Paper Matching System [5], an automated paper reviewer assignment system, has been used for some famous academic conferences,

In latest years, researchers are concerning on some new aspects of CPAP. [6] proposed a topic coverage paper reviewer assignment. They studied the maximal topic coverage for goodness and the conflict-of-interest for the fairness in the assignment, and proposed an approximate algorithm to solve the problem efficiently. Drawing inspiration from multi-criteria decision making and social choice theory, [7] used order weighted averages (OWAs), a parameterized class of mean aggregators, to propose a novel mechanism to solve the CPAP problem. [8] also took an OWA aggregation function to summarize information from different sources and ranked the candidate reviewers for each paper, and thus developed a decision support tool for conference review assignment. [9] focused on a fairness objective—to maximize the review quality of the most disadvantaged paper, and designed an assignment algorithm based on an incremental maxflow procedure. [10] reduced the CPAP to a network flow, and use a polynomial-time algorithm to compute the maximum flow through the network. This research points out that minimum cost flow is a feasible approach for many criteria of CPAP. [11] proposed a fair paper matching model with local fairness constraints. They presented two approximation algorithms for solving this model, a cyclic relaxation method—FairIR, and a minimum cost flow-based heuristic method—FairFlow. About minimum cost flow problem, many other effective algorithms have also been applied to solve it, e.g., the interior point method [12]. This kind of algorithm is also promising for the CPAP.

In the paper assignment, it is very common that many papers being assigned are not liked by some reviewers due to their personal interests or specialties. In fact, this kind of problem has been studied as a fair allocation problem of indivisible goods, which is a hot topic in the field of artificial intelligence [13]–[15]. Many researchers have studied some well-known criteria of fairness in fair allocation, in which one of the most important ones is envy-freeness (EF). Envy-freeness, an appealing fairness concept in allocation, ensures no agent can obtain more utility by exchanging their items for those of another. There are many works of literature related to envy-freeness in the allocation of indivisible goods [16]–[18]. However, envy-freeness is a strong notion of fairness, and it may not be achievable on some allocation instances [19]. Therefore, some other weaker notions of fairness, such as proportionality [20], max-min and min-max fair share [16], [21] and epistemic envy-freeness [19], are proposed by researchers to assess the fairness. Pareto efficiency, another important notion in fair allocation, means that no agent can be made better off without another agent being made worse off. Envy-freeness combined with efficiency leads to a natural notion of fairness [22], and it is very important to ensure all agents have incentives to participate in the allocation, so as to improve the total welfare. However, in many cases, efficiency and envy-freeness cannot be simultaneously achieved [23]. Therefore, finding a balance between them becomes a very important issue.

In this paper, we consider a conference paper assignment problem in which we minimise the amount of envy reviewers have for others. The main contributions of this paper can be summarized as follows: 1) A bi-objective model—minimal-envy conference paper assignment is proposed to guarantee both the efficiency and fairness in conference paper assignment. 2) A fast two-stage iterative algorithm is proposed to achieve high computational efficiency, especially on large-scale problem instances.

II. Problem Formulation

In this work, we consider the conference paper review assignment problem with minimal envy. Before the problem formulation, several assumptions are defined as follows to clarify the problem.

- A constraint of reviewer quantity exists, which means each paper should be assigned to a given number of reviewers.
- A constraint of reviewers' workload exists, which means that each reviewer can be assigned with a given number of papers.
- The reviewers who bid a paper positively will be given priority to review the paper, but the other reviewers may also be assigned with the paper.

The notations used in the model are given in Table I.

A. *Efficiency and Fairness Concepts*

Consider allocating m papers in set P to n reviewers in set R. An allocation can be denoted by $A = \{A_1, A_2, \cdots, A_n\}$ with $P = \cup_{i \in R} A_i$, where A_i is the sub-set of papers allocated to reviewer i. For each reviewer i, it has a utility function u_i, $u_i(A_i)$ means the utility of reviewer i for the papers allocated to them. It might seem odd to consider being allocated a paper to review as having (positive) utility. However, as agents get a fixed number of papers to review, their utility is in getting ones that they like. The total utilitarian welfare for an assignment can be defined as

$$\mathrm{UW} = \sum_{i=1}^{n} u_i(A_i). \tag{1}$$

In an allocation problem, it is natural that the UW should be maximized to guarantee the efficiency.

Let us consider another concept of allocation—fairness. In this paper, we consider one reviewer might envy another reviewer with a better set of papers than his. For reviewer i, a better set of papers for him means higher $u_i(A_i)$. Consequently, if two reviewers have utility for a paper but only one of them is allocated this paper to review, then one reviewer might envy another.

For fairness concept, we recall some well-known definitions in resource allocation.

Definition 1: ***Envy-freeness (EF):*** An allocation satisfies envy-freeness if $u_i(A_i) \geq u_i(A_j)$ for any pair of agents i and j, $i, j \in N$.

However, in some practical problems, an envy-free assignment may not exist, e.g., consider a problem in which reviewer

Variable	Description
R, P	Sets of reviewers and papers.
R_c, P_c	Paper demand constraint and reviewer workload constraint.
A_i	The sub-set of paper assigned to reviewer i.
$u_i(A_i)$	the utility of reviewer i with the papers allocated to him.
u_{ik}	Utility of assigning paper k to reviewer i.
x_{ij}	Binary decision variable, $x_{ij} = 1$ denotes paper j is assigned to reviewer i, and viceversa.

TABLE I
Notations in model

1 has utility 0 and 1 for paper a and b, whilst reviewer 2 also has utility 0 and 1 respectively. We assume that a paper can only be assigned to exactly one reviewer, there are only two valid assignments allocating paper a to reviewer 1 and paper b to reviewer 2 or paper a to reviewer 2 and paper b to reviewer 1. Both of these assignments will cause envy. Therefore, there is no envy-free assignment in this problem.

In this context, we need a more relaxed measure of the amount of envy in an allocation.

The concept of the Gini index (GI) is one powerful way to deal with this kind of problem. The GI is one of the most frequently used measures to assess the inequality. Motivated by the definition of GI, which is used for assessing inequality in the distribution of wealth, [24] defined a related index that measures the amount of envy.

Definition 2: ***Envy Index(EI):*** An index to evaluate the envy of reviewer i to reviewer j is defined as $max\{0, u_i(A_j) - u_i(A_i)\}$. Drawing on the definition of GI, the total envies from all pairs of agents can be defined as

$$\mathrm{EI} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \max\{0, u_i(A_j) - u_i(A_i)\}}{\sum_{i=1}^{n} \sum_{j=1}^{n} u_i(A_j)} \tag{2}$$

Compared with envy-freeness, EI is a more powerful measure—if an allocation is envy-free, the envy index will be zero, otherwise, the envy index varies in (0,1] to indicate how serious the envy exists, this should be very valuable in some practical scenarios if there is no envy-free assignment. This index has many other features as well, such as any allocation which minimizes the envy index is Pareto efficient. Furthermore, in some large-scale practical problems, it is usually very difficult to find an envy-free allocation even if it exists. The definition of EI could be helpful to design an optimization algorithm—it provides an effective measure to evaluate two allocations which both are not envy-free, which evaluation is a very common operation in many optimization algorithms.

B. Problem Formulation

In this work, we try to minimize the Envy index and maximize the utilitarian welfare of reviewers in the conference paper assignment procedure, which is a bi-objective optimization.

The problem can be formulated as

$$\max \mathrm{UW} = \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} \cdot u_{ij} \tag{3}$$

$$\min \mathrm{EI} = \frac{\sum\limits_{i=1}^{n} \sum\limits_{j=1}^{n} \max\{0, \sum\limits_{k=1}^{m} (u_{ik} \cdot x_{jk} - u_{ik} \cdot x_{ik})\}}{\sum\limits_{i=1}^{n} \sum\limits_{j=1}^{n} \sum\limits_{k=1}^{m} u_{ik} \cdot x_{jk}} \tag{4}$$

s.t.

$$\sum_{i=1}^{n} x_{ij} = R_c, j \in [1, m], \tag{5}$$

$$\sum_{j=1}^{m} x_{ij} \leq P_c, i \in [1, n], \tag{6}$$

where x_{ij} is the decision variable, and u_{ij} is the utility variable.

Eq. (5) is the reviewer quantity constraint, which restricts each paper should be assigned to R_c reviewers.

Eq. (6) is the reviewers' workload constraint, which limits the maximum quantity of papers a reviewer can accept.

III. A Fast Iterative Algorithm

Considering the large-scale combinational optimization of a practical conference paper assignment problem, an efficient algorithm is very necessary in practice. [24] has pointed out that finding an allocation minimizing the envy index is NP-hard. It immediately follows that solving the bi-objective model is also NP-hard. In this paper, we propose a two-stage iterative algorithm to solve the CPAP. The general flow of the algorithm is shown in Figure 1. As is shown in the figure, each iteration contains two stages to maximize UW and minimize EI respectively.

The first stage corresponds to a min-cost flow problem(MCFP). In this stage, we test whether there is an allocation that satisfies all constraints, then the utilitarian welfare is maximized in a precise way: Reduce the assignment model to a network flow problem, and compute the maximal UW by the cheapest augmenting path algorithm. The model constraints are also considered by setting the capacity of arcs. After this stage, we can obtain an allocation with maximal UW if a valid allocation exists.

Fairness is considered in the second stage. Due to the complex nonlinear fairness objective, it is hard to compute the minimal EI using network flow methods. However, we can find that all binary decision variables x_{ij} are fixed in stage 1, then the fairness metric EI of different allocations can be easily evaluated. To minimize envy among reviewers, we put forward one more metric to assess partial envy, and use the metric to generate a weight coefficient that is used to update the weights of arcs for the next iteration.

The iteration is repeated until meeting one of the stopping criteria—an envy-free allocation is found or the maximum iteration number is reached. In this algorithm, each iteration generates one allocation, and after the whole iteration, a set of allocations will be obtained.

A. Stage 1: MCFP for Maximal Utilitarian Welfare Assignment

According to [10], MCFP can be adapted for some kinds of CPAP, including maximizing UW. In this work, we reduce the problem to a maximum network flow problem to test whether there is a valid allocation. The instance of maximum network flow for CPAP is shown in Figure 2, it consists of several components as follows.

- n nodes $\{R_1, R_2, \cdots, R_n\}$, each node corresponds to a reviewer.
- m nodes $\{P_1, P_2, \cdots, P_m\}$, each node corresponds to a paper.

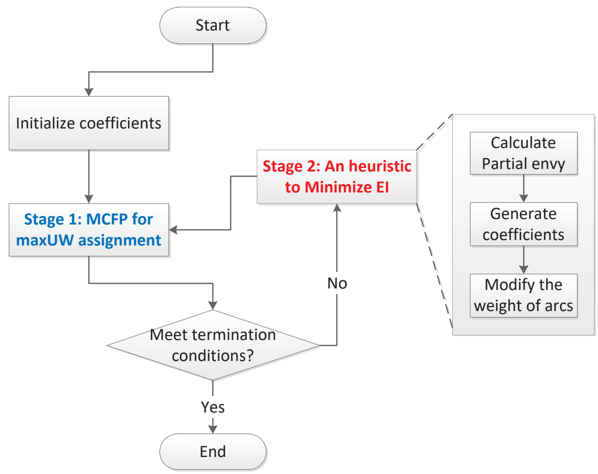


Fig. 1. The general scheme of the two-stage iterative algorithm

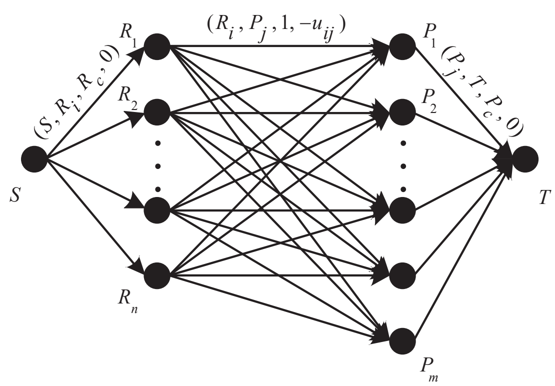


Fig. 2. An instance of maximum network flow for CPAP

- Two extra nodes, the source S and the sink T.
- $n \times m$ arcs with capacity 1 from R_i to P_j, $i \in [1, n], j \in [1, m]$.
- n arcs with capacity R_c from S to R_i, $i \in [1, n]$.
- m arcs with capacity P_c from P_j to T, $j \in [1, m]$.

Obviously, any allocation will follow the model constraints if the corresponding flow satisfies that all arcs from R_i to T are full-flowed. It is also easy to know each maximum flow makes all arcs from R_i to T full-flowed if a valid allocation exists. Nevertheless, it should be noted that such an instance does not consider the preference of each reviewer for papers.

To achieve maximal UW, we assign cost $-u_{ij}$ to each edge from R_i to P_j and cost 0 to other edges. Then the opposite of the total cost will be equal to UW. Therefore, the minimal total cost will also equal to maximal UW. The cheapest augmenting path algorithm (CAPA) [25] is used to solve MCFP. The procedure of this algorithm are given in Algorithm 1. Considering that the network contains negative weight arcs, we use Bellman-Ford algorithm [26], [27] to find the cheapest path from source to sink.

Algorithm 1 The cheapest augmenting path algorithm (CAPA)

Input: source,sink
Parameter: Flow F; Edge E,A; Node U; Path P;
Output: flow,cost

```
F ← 0. /* Initialize the flow with zero flow */
cost ← 0
Add a reverse edge for each edge
while Have a nonzero capacity path from Source to Sink do
  Bellman-Ford(Source,Sink)
  U ← sink
  while have a non-zero capacity path from source to U do
    P ← cheapest path from source to U
    minf ← minimum of (cap - flow) for all edges in P
    for all Edge E ∈ P do
      E.flow ← E.flow + minf
      Ē.flow ← Ē.flow - minf
      /* Ē is the reverse edge of E */
      cost ← E.cost × minf
    end for
    A ← the first edge which edge.flow=edge.cap
    U ← A.from
    flow ← flow+minf
  end while
end while
return F
```

B. Stage 2: An Heuristic to Minimize Envy Index

This traditional MCFP can only handle single-objective optimization problem. But our model considers both $\max$ UW and $\min$ EI objective. In order to promote a fairer treatment for all reviewers during the whole allocation process, we put forward some metrics in each iteration.

Competitive envy is a metric to describe the envy between a pair of reviewers caused by competition for a paper. Compared with EI, it can better measure the envy at a micro level.

*Definition 3: **Competitive Envy: (CE)*** Given iteration t and paper k, the competitive envy of reviewer i to reviewer j can be defined as

$$CE^t_{ijk} = \begin{cases} 0 & \text{if } u_i(A_i) \geq u_i(A_j) \text{ or } x_{ik} = 1 \text{ or } x_{jk} = 0, \\ u_{ik} & \text{otherwise.} \end{cases} \tag{7}$$

$CE^t_{ijk} > 0$ if and only if reviewer i has positive utility on paper k, and paper k is assigned to reviewer j but not i. However, there is one exception—if $u_i(A_i) \geq u_i(A_j)$, reviewer i's competitive envy to j about any paper will never be considered.

Next, we propose another metric—partial envy to evaluate the competitive envies of a reviewer to all the other reviewers.

Definition 4: ***Partial Envy: (PE)*** Given iteration t and paper k, the partial envy of reviewer i can be defined as

$$PE_{ik}^{t}=\sum_{j\in R}CE_{ijk}^{t} \tag{8}$$

It is easy to deduce that PE can refer to envy-freeness in some specific conditions.

Theorem 1: Envy-freeness is a necessary and sufficient condition of

$$PE_{ij}^{t}=0,\forall i\in R,j\in P. \tag{9}$$

Proof. We prove the sufficient condition at first. If an allocation A is envy-free, from Eq. (2), it can be known that $u_i(A_j)\leq u_i(A_i),\forall i,j\in R$. According to Eq. (7)-(8), Eq. (9) is naturally satisfied.

Next, we prove the necessary condition by contradiction. If an allocation A satisfies Eq. (9), it is easy to derive that $CE_{ijk}^{t}=0$, this is to say, $\forall i,j\in R,k\in P, if\ u_i(A_j)>u_i(A_i), x_{ik}=1\ or\ x_{jk}=0\ or\ u_{ik}=0$. Now we assume the allocation A is not envy-free, that is, $u_i(A_j)>u_i(A_i),\exists i,j\in R$. This condition is equivalent to $\sum_{k=1}^{m}u_{ik}(x_{jk}-x_{ik})>0,\exists i,j\in R,\forall k\in P$. However, for these i,j,k, at least one of $x_{ik}=1$, $x_{jk}=0$, $u_{ik}=0$ must be satisfied. At the same time, $u_{ik}(x_{jk}-x_{ik})$ could not be positive when any one of the above three conditions is true. Then we can conclude that this assumption A is not envy free conflicts with Eq. (9), so envy-freeness is a necessary condition of Eq. (9). □

Based on theorem 1, we propose an effective heuristic and attempt to make the PE of all reviewers to be zero. The heuristic is to set a weight coefficients on UW. We define UW^t to represent the weighted utilitarian welfare in tth iteration. The maximum of UW^t can be computed using algorithm 1 in stage 1, then we can control the allocation to assign a paper to a specific reviewer with a higher probability by adjusting the coefficients.

Definition 5: ***Weighted utilitarian welfare: (UW^t)*** The UW^t can be defined as

$$\mathrm{UW^t}=\sum_{i=1}^{i=n}\sum_{j=1}^{j=m}\alpha_{ij}^{t}\cdot x_{ij}^{t}\cdot u_{ij}, \tag{10}$$

where α_{ij}^{t} is a weight coefficient for assigning paper j to reviewer i in the tth iteration, it lies in (0,1]. The details of the weight coefficients generation are given in algorithm 2. α_{ij}^{t} will iteratively reduce in the algorithm, and its reduction in next iteration depends on the value of PE_{ij}^{t}, the greater PE_{ij}^{t}, the smaller reduction of α_{ij}^{t}. In the algorithm, all weight coefficients should be initialized to 1, the parameter θ, ranges from 0 to 1, is defined to control the change range of the coefficients.

Since there is no guarantee that envy-free assignment exists, several termination criteria are set for the algorithm as follows.

- EI = 0, which means an envy-free assignment is obtained.
- The number of iterations reaches a maximum value I_{max}.

Algorithm 2 The weight coefficients generation algorithm

Input: $x_{ij},u_{ij},\alpha_{ij}^{t},i\in R,j\in P$;
Output: α_{ij}^{t+1};

for all $i\in R,j\in P$ **do**
  $PE_{ij}^{t}\leftarrow 0$
end for
for all $i,j\in R$ **do**
  if $u_i(A_j)>u_i(A_i)$ **then**
    for all $k\in P$ **do**
      if $x_{ik}=0$ and $x_{jk}=1$ and $u_{ik}>0$ **then**
        $PE_{ik}^{t}\leftarrow PE_{ik}^{t}+u_{ik}+\max\{u_{ik}-u_{jk},0\}$
      end if
    end for
  end if
end for
$maxPE^t\leftarrow\max_{i\in R}\max_{j\in P}PE_{ij}^{t}$
for all $i\in R,j\in P$ **do**
  $\alpha_{ij}^{t+1}\leftarrow\alpha_{ij}^{t}\cdot[\theta+(1-\theta)\cdot\frac{PE_{ij}^{t}}{maxPE^t}]$
end for

IV. Experiments

A. Experimental Datasets

Preflib, an open library for preferences [28], provides several collections of real conference bidding data, in which we choose three datasets from an AI conference as our experiment data. The bidding language for the conference is $yes/maybe/conflict$. In order to make the dataset more useful for PreLib users, the data has been converted to incomplete partial orders $yes>maybe>no\ response$, and the papers of which a reviewer had a conflict have been removed from their preference list, so each paper can be assigned to any reviewer. In this work, we use the utilities $2,1,0$ for preferences $yes, maybe, no\ response$. Three datasets with different scale are selected to perform the experiments. The details of the datasets refer to Table II.

B. Experimental Algorithms and Settings

To evaluate the algorithm performance, NSGA-II, one of the most popular and classical evolutionary algorithm in multi-objective optimization, is taken to compare with ours. CPAP has been modeled as some of these problems, e.g., the Toronto Paper Matching System. As in the Toronto system, the basic problem with single objective to maximise UW is modeled as the same as ours except the objective EI, and it is solved by linear programming (LP) [5]. CPLEX is a powerful optimization tool that integrates various solvers,

Dataset	Papers	Reviewers	Identity
1	54	31	MD-00002-00000001
2	176	146	MD-00002-00000003
3	613	201	MD-00004-00000001

TABLE II
DETAILS OF THREE DATASETS

Dataset	Topsis weight	Ours			NSGA-II		
		UW	EI	GI	UW	EI	GI
1	[1,0]	173	0.0156	0.2431	170	0.0866	0.1560
	[0.5,0.5]	171	0.0026	0.2079	166	0.0076	0.1351
	[0,1]	169	0.0000	0.1935	162	0.0000	0.1323
2	[1,0]	625	0.0106	0.2947	601	0.1909	0.3717
	[0.5,0.5]	618	0.0032	0.2784	582	0.1292	0.3430
	[0,1]	606	0.0000	0.2480	543	0.1028	0.3307
3	[1,0]	1817	0.0013	0.2699	1701	0.0505	0.1233
	[0.5,0.5]	1809	0.0003	0.2454	1615	0.0245	0.1018
	[0,1]	1794	0.0000	0.2444	1450	0.0134	0.1012

TABLE III
THE RESULTS OF BI-OBJECTIVE MODEL WITH DIFFERENT TOPSIS WEIGHTS

Dataset	Ours, ω = [0.5,0.5]			CAPA(maxUW)			LP solver(maxUW)			CP solver(minEI)		
	UW	EI	GI	UW	EI	GI	UW	EI	GI	UW	EI	GI
1	171	0.0026	0.2079	173	0.0744	0.3599	173	0.0804	0.3002	147	0.0000	0.1093
2	618	0.0032	0.2784	625	0.0852	0.4672	608	0.1140	0.3292	–	–	–
3	1809	0.0003	0.2454	1817	0.0079	0.2699	–	–	–	–	–	–

TABLE IV
THE OPTIMAL RESULTS OF SINGLE-OBJECTIVE MODEL

such as linear programming (LP), mixed integer programming (MIP) and constraint programming (CP). Thus, to provide more comparison in detail, we compute the upper bound of UW by the LP solver of CPLEX and the CAPA in this work, and solve the lower bound of EI by the CP solver of CPLEX. All the experiments are conducted on a PC with Intel Core i5-6500 CPU @ 3.20GHz and 8GB RAM.

The iteration times to 2000 and population size to 30 in NSGA-II. For our algorithm, $\theta = 0.9$, and $I_{max} = 1000$. $P_{max} = 5, R_{max} = 2$ for dataset 1-2, and $P_{max} = 7, R_{max} = 2$ for dataset 3 due to deficiency of reviewers.

C. Experimental Results

Since the bi-objective optimization algorithm obtains a solution set, we choose the TOPSIS method to select a optimal solution from the solution set. We use three different TOPSIS weights, ω = [1,0], [0.5,0.5], and [0,1], to choose the optimal solution. ω = [1,0] represents efficiency first, [0.5,0.5] denotes efficiency and fairness are considered equally, and [0.5,0.5] means fairness first. The results of single-objective problems and bi-objective problems are shown in Table IV and Table III, respectively. It should be noted that if solving minEI model by the CP solver of CPLEX, UW is approximately equal to zero. Therefore, we set a new constraint $UW > L$, and enumerate L from big to small until CPLEX can find a valid assignment. The cell without data means that CPLEX cannot find any valid assignment within limited time.

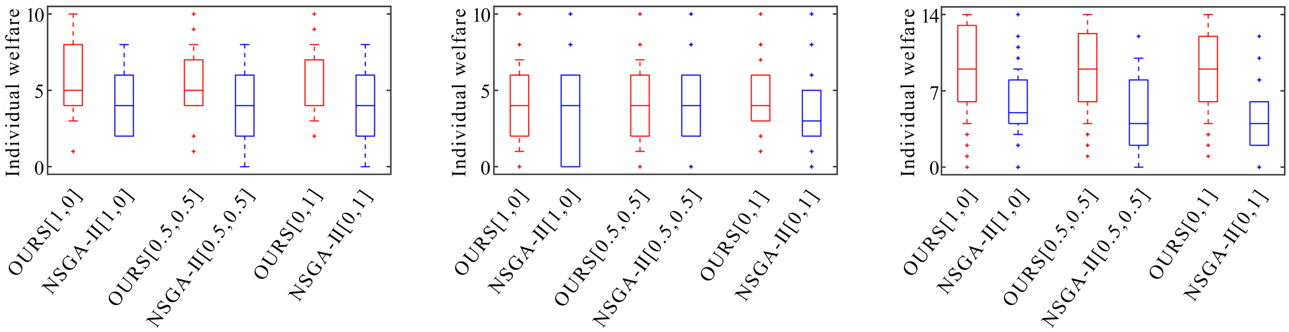
From Table III and Table IV, when the ω = [1,0], we can see that our algorithm achieves maximum utilitarian welfare in all three datasets, this is easy to understand from Section III—the first iteration of our algorithm is actually a CAPA to maximize utilitarian welfare. We can also find that for all three TOPSIS weights, the metrics of our algorithm are better than NSGA-II, either on UW or EI. Another phenomenon in Table III is that our algorithm achieves larger GI than NSGA-II on dataset 1 and dataset 3, but viceversa on dataset 2. We think this is reasonable because this work focuses on the fairness that represented by envy index, but not the absolute equity denoted by GI. Table IV shows that our algorithm achieves both high efficiency and fairness compared with single objective optimization Take ω = [0.5,0.5] as an example, for the fairness aspect, our algorithm outperforms the single-objective CAPA on both EI and GI metrics. Not only that, but the UW obtained by our algorithm is substantially higher than that of simple using CP solver to minimize EI.

For large-scale practical problems, the computing performance is also a very important metric to assess an algorithm. The time consumption of different methods are shown in Table V. Our algorithm is an iterative algorithm, it is actually a MCFP solving during each iteration, so we can see that the computing time of our algorithm is obviously greater than CAPA. From the table we can see that our algorithm is significantly faster than NSGA-II, which means our algorithm is more practical to solve large scale engineering problems.

From these results, we can basically conclude that our proposed algorithm is an efficient-fair method for CPAP, especially for large-scale practical problems.

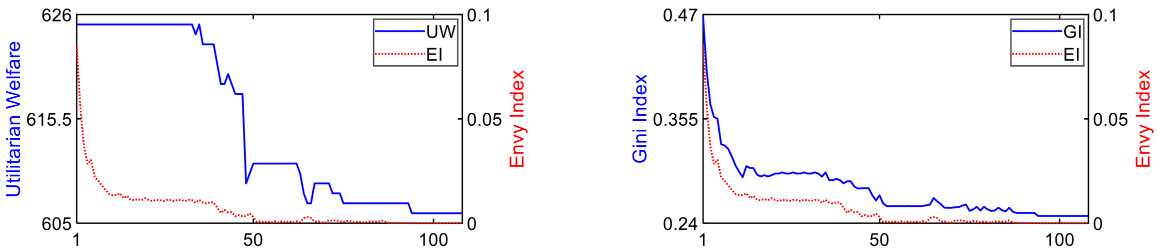
Dataset	Ours	NSGA-II	CAPA
1	0.68	121.40	0.01
2	35.37	2253.65	0.22
3	446.73	14937.80	5.49

TABLE V
TIME CONSUMPTION OF DIFFERENT METHODS(SECS)



(a) Individual welfare on dataset 1 (b) Individual welfare on dataset 2 (c) Individual welfare on dataset 3

Fig. 3. Box plot of individual welfare



(a) Utilitarian welfare and Envy Index (b) Gini Index and Envy Index

Fig. 4. The variation of metrics during the whole iteration on dataset 2

D. Statistical Analyses of Performance Metrics

The results in Table III only show the overall objectives of the assignment, but don't provide the assignment details, i.e., the distribution of individual welfare, and the individual envy among reviewers. In order to show the details of assignment, we use box plot to portray the reviewers' individual welfare in Figure 3. From Figure 3, we can see that the upper quartile, median and lower quartile of ours are higher than NSGA-II, which means more individual welfare is obtained for the reviewers, especially on dataset 3. Furthermore, we can see that the box of ours with ω = [0,1] is shorter than ω = [1,0] on all the datasets, which means the individual welfare of reviewers is closer to each +other, that is, the better fairness of the paper assignment is achieved.

Next, we use a convergence curve to observe the iteration of the algorithm. In Figure 4(a), there is a basic trend of decline on both UW and EI, which represent the efficiency decreases and the fairness improves. In Figure 4(b), the curves of the metrics EI and GI also show a trend of decline. In general, the curves of the two metrics are basically similar, but there are still some differences between them. Consider the different definition and meaning of the metrics, given any two allocations, the evaluation results using EI and GI could be inconsistent. From the above results, we can conclude that our algorithm performs better on both efficiency and fairness than NSGA-II. In addition, since our algorithm has less time consumption than NSGA-II, we also say that it is more conducive to solve large-scale practical problems.

Finally, it is worth noting that from Table III we can see envy-free assignment exists on all three datasets, this may be due to the constraints of the model are relatively loose. From this observation, it appears that we can directly replace EI with envy-freeness. However, for some problem instances, there may be no envy-free assignment. Even an envy-free allocations exists, due to the huge searching space, it is difficult to directly find an envy-free allocation in the algorithm. Thus, envy index would be very useful and helpful for the algorithm design, i.e., provides a way to evaluate the fairness of a not envy-free assignment.

V. Conclusions

This paper proposed a bi-objective conference paper assignment model—with the both consideration of fairness and efficiency. On fair aspect, we use a new metric—envy index to evaluate the severity of envy in assignment. Consider the complexity of envy index and the difficulties of bi-objective optimization, we proposed a fast iterative algorithm to solve the problem. The experimental results proved that our algorithm is efficient-fair, especially for large-scale practical problems. Consider many academic conferences are facing huge paper submissions and deficient reviewers, how to efficiently assign the papers and improve the satisfaction of both reviewers and authors have been a focus area in conference management. Our proposed model and algorithm is helpful to deal with this problem. The method proposed in this paper is also meaningful for a number of similar allocation or matching problems, e.g., research project review assignment and order dispatching.

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