International Journal of Science and Research (IJSR)
ISSN: 2319-7064
ResearchGate Impact Factor (2018): 0.28 | SJIF (2018): 7.426

Presenting a New Model for the Management and Selection of Experts in Big Data

Nasrin Hashempour[1], Parisa Safarzadeh[2], Hanieh Raoofifard[3]

[1]DadehPardaziToosRaham, Mashhad, Iran

[2]Department of Computer Science, Neyshabour University

[3]Department of Computer Science, Birjand University

Abstract: ***Finding a group of experts is one of the defined issues in the social fields. The aim is to appoint a group of experts, each having specific skills to do a variety of tasks, which for any of these tasks they require some particular expertise. This appointment is considered as NP-Hard issue, and its exact solution is exponential. Most-used cases for the selection of experts in Big Data apply the top-down greedy algorithm. The problem in these methods is the lack of attention to the specific skills and increase in runtime when using thegreedy algorithm; because sorting is based on more skills of each reviewer and there is no consideration to the number of skills from a special type. In this paper, we have used a model based on knapsack problem theory as well as applying an artificial bee colony algorithm to appoint a group of experts to review scientific papers. In this study, the algorithm continues until the selection of a set of the experts who cover all the skills required to reviewing papers; therefore, scoring the reviewers at each stage plays a significant role in determining the near-optimal set of answers. Also, to score the experts in Big Data, we have considered the two criteria of coverage and specific skills of experts. In the assessment section, the result of the implementation of the proposed algorithm on a standard dataset has been investigated, and the results were compared with the greedy algorithm. The assessment results have shown that the proposed algorithm in terms of time and accuracy of selected experts, was superior to the greedy algorithm.***

Keywords: Big Data; Experts; Reviewing; Scientific papers; Knapsack problem; Artificial bee colony algorithm; Coverage; Being special;

1. Introduction

With the development of Big Data and increase in knowledge sharing by experts in the technical and scientific associations and groups as well as people participating in the discussions, the social networks have become a platform for finding people with the appropriate expertise. Experts provide the possibility of their visibility by placing the resume and history of their performance on the social networks. They turn the social networks into an environment for finding experts.

Formation of specialist groups to get things done is a complex task with limited time. The more the tasks be complicated, the more people with specialized expertise are required. Also, if more expertise is selected, there will be a higher probability of success[1].

Finding a group of experts is one of the defined issues in the field of the social networks with the aim of appointing a group of experts to perform a task. The answer to this issue can be useful in different areas such as finding the right people to conduct the projects, finding judges to review the papers, and finding suitable locations to build factories and workhouses that should be away from residential areas. Appointment of experts to conduct reviewing papers is based on the skills that article required, and its exact solution has an exponential time order.

In this study, we achieve the optimal response with polynomial time order using the bee colony algorithm. Also, we consider the unique skills of the reviewers i.e., the skills that the fewer number of reviewers have. Reviewers who have such expertise should be a priority choice. In such a way, the articles which require specific expertise allocated to them. In this paper, we look for a method that suggests an algorithm for the selection of experts in reviewing papers by taking into account the two features of being unique reviewer and coverage[2].

We have considered the theory of Knapsack problem based on the bee colony algorithm as an optimal solution in the coverage of expert to review the scientific papers. This algorithm selects suitable experts to review papers based on how unique they are. Thus, this algorithm considers the conditions, and at the beginning, allocates papers that require particular expertise toexperts who have those. Then other papers are given to appropriate experts according to the expertise needed[3]. Taking advantage of the bee colony algorithm, and considering the two criteria of experience and uniqueness result in high efficiency in choosing reviewers for scientific papers.

2. Earlier Works

There are many methods to determine the impact of the social networks' users. Although we can increase the recommended results by considering the trust and impact of users, creating an appropriate measurement model is challenging. Besides, in recommender systems that consider the user's influence, it is difficult to have an integrated and stable suggestion to effectively and regularly change the users. Therefore, evaluating and taking advantage of the user's social data (which present on some websites that the experts record their expertise) is essential and vital for the social recommendations[4,5].

Raw data turn into information and become meaningful after processing. When information, experience, and insight about a subject are in one's possession, it is said that the person knows that matter. Therefore, the use of expert finder systems will be much more useful instead of text retrieval systems, because these systems introduce the experts to answer the knowledge questions and needs of users rather than answering the questions. In recent years, given the importance of expert recommender systems, many researchers have been attracted to this area[6].

2.1 The Expert Finder Systems

The mission of the expert finder systems is to recommend specialists in specific areas. These systems save and refine previous answers and questions of the users and predict their areas of expertise. Upon receiving new questions, the experts who have expertise in this area are identified and selected to meet them. This makes that questions presented to people with knowledge rather than offer to all users, and this, in turn, increases the speed and accuracy of the response. Also, the communication of experts causes that expert transfer their knowledge, insight, and experience and use face to face and non-virtual relations in this way or introduce other experts in case of inability to respond.

Expert finder systems use the following methods to find specialists[7]: The content analysis method, the network analysis methods and combined analysis methods.

2.1.1The Expert finding based on content analysis

In this method, we create a profile for each expert, including personal information and his favorite contents. This has been done by monitoring and collecting the pages visited by the expert.Then, we use this information as the areas of expertise as well as calculating the similarity of his knowledge areas. The most popular data recovery model that has better results than other models, is the vector space model. In this model, all the documents and users' queries are considered as a vector in words space[8].

2.1.2 The Expert finding based on network analysis methods

Graph analysis methods are used recently for improving the expert finding algorithms. These studies have shown that in areas such as the social networks that people have social connections with each other, using algorithms based on graphs had better results.

Page Rank is a web-based democratic structure which uses WAN link to determine the order and the rank of a given page. In this algorithm, the link structure between web pages has been used to determine the significance of web pages.

Gorgik and Agishtin by creating a communication link between the sender and the receiver in the e-mail network and between the questioner and the respondent in Yahoo forum formed a social network and using the algorithms HITS, found everyone's expertise by determining a profile for each person[9].

Shafiq et al.[3]determined each expert scores using the user's writing history and personal information as well as creating knowledge profiles for each user for its content analysis. Then, they find experts by analyzing questions and answers links and using the relationship between queries and former queries. They also used selected answers of individuals as the best responses and calculated their reputation.

Also, Wang et al. presented the Expert Rank model based on the Page Rank algorithm where they used a combination of content analysis and network analysis. The results were better than both network and content analysis [10].

2.1.3 Expert finding based on combined methods

In recent studies, combined methods have been used for finding an expert. In these studies, both content analysis and network analysis methods were used. This method has been used in Big Data, where people have both profiles and written information as well as social relations. Using combined methods had better results than previous methods[11].

According to these practical purposes for designing expert finder systems and selected user's choice, several algorithms suggest optimal solutions for allocation problem. In this study and a model that is considered for selection of experts to review the papers, we have used the Knapsack theory as well as the bee colony algorithm where the most optimal form of allocation of expert's priority with desired specialties to review scientific papers have been considered.

2.2 The Expert finder systems algorithms

Algorithms used in many investigations apply greedy top-down method. The main issue in these methods is that they do not pay attention to the uniqueness of skills. Because ordering is based on the number of skills of each reviewer and the skills from one type (uniqueness of the skills) are neglected[12].

The social recommender algorithm is based on social trust and impact including trusted or effective user ratings to complete and present the user's preferences. Collaborative filtering is the most complete and popular method in the recommender systems due to its simplicity and effectiveness. This method is based on the assumption that the target user prefers items that other users with similar preferences have elected them. However, collaborative filtering is efficient in the recommender systems, but still has inherent problems such as launching and distribution of data[13].

He and Chu suggested a social recommender system using user influence as a factor. They have proven the results of their research superiority that has been by using collected data from yelp.com, comparing similarity-based collaborative filtering that only takes into account the ranking data[14].

Algorithms for extraction of known repetitive pattern, such as Aprior, Fp-Growth or some methods that parallel these algorithms are used for the selection of experts on social networks. Since social networks data are increasing and constantly being updated, CAT or CAN algorithms can be used to maintain the same node in the network[15,16].

Recent research shows that using node or edge content on the social network can contribute in the increase in discovery of user community and influential people. Researchers suggest methods that are based on possible patterns of Bayesian[17]. These patterns or procedures gives the possibility of interference to their community members. However, in these methods, the chart structure is very mindful. Using this model, in some studies, identification and selection of influential people in the online social network have been done according to user activities[18].

3. The Proposed Model

According to the practical purposes for designing the expert finder systems, and selecting the chosen users, several algorithms offer optimal solutions for allocation problem. This study and the model that is considered for the selection of experts to review the papers have used the knapsack theory and the bee colony algorithm which considered the most optimal form of allocation of experts with expertise in priority to review the scientific papers.

The social network is considered by graph G where n shows nodes of the graph, experts with different skills are K = {k_1, ..., k_n} so that the set of a k_i person's skills M_i is shown as M_i = {m_1, ... m_n}.It is assumed that the skills of each person are saved as local data on the node related to him. To do the work W, we have used a subset of experts (K ') with required skills M.' The set of M' is obtained as follows:

$$M' = \cup M_i \text{ such that } k_i \in k \quad (1)$$

This problem can become a coverage problem which is NP-Hard[19]. Therefore, we should use non-exact and approximate methods to solve it. Eventually, by comparing the results of solving the problem with results obtained through other algorithms that their validity has been proven or questioning from experts (workforce), we can examine the results. The method used to solve the problem can be approximated by using the theory of the bee colony algorithm and the Knapsack problem.

In addition, one of the raised issues is the lack of attention to the unique required expertise for reviewing papers. The proposed algorithm has the particular attention to the issue of required expertise to review the articles.These data have already been collected and are available and usable in a zero-one Knapsack which is the input of the bee colony algorithm.

In the implementation of the model in this study, we have used the Big Data analysis method to collect the required information on social networks. After collecting the desired information, such as the user's profile data and expertise, we have stored these data in a file named Reviewers. The data are used then to select the experts to review based on their expertise.

In designing an algorithm for selecting experts to review the papers, in addition to the user data and their expertise, we need to collect the required expertise for reviewing the papers. These data are stored in a file called query Aspects. Finally, the algorithm identifies required expert for reviewing papers according to the required expertise and obtained information on experts and their expertise.Then, the accurate choosing among the required expertise for the reviewing of a paper and those that specialist have as well as the bee colony algorithm can give the reviewers the required resources.

3.1 The proposed bee colony algorithm

As it can be seen in Figure 1, on the left side as the input as of algorithm, we have collected and stored user data including the expertise of experts in social networks like Facebook in a file named Reviewers.txt. There are also main resources of paper's expertise required, that these resources have been gathered based on reviewing papers and they are available in the file named QueryAspects.txt. Also, we have used the bee colony algorithm.

Suppose that the algorithm has two matrices of expert's skill sets and skill sets required for reviewing the paper. Reviewers matrix (D) is a matrix with (0,1) elements which indicates the experts' skills. If the reviewer has K skill, the number of 1 would be placed in K_n column otherwise we would have 0 there. Earlier in preprocessing, the required skills for papers that may have been not existing in the list of reviewers'skills has been completely deleted. Because surely, we cannot find any solution to cover these skills completely.

For example, if the column related to skill X of the matrix D has just 1, means that the X skill is exceptional and the reviewers that have this skill must be selected. Accordingly, the score of α^{-n} is attributed to any skill. In the experimental results, α in α^{-n} has been equal to 10 and n represents the number of repetitions of X skill. Then, if X skill is in the expertise of two different reviewers, the weight would be considered 0.01, and if the expertise is for three reviewers, the weight is 0.001 to it.

In addition to this horizontal sum of each row represents a number of skills of an expert. If the total amount in the elements of a row is significant, according to our criteria of maximum coverage, it means that reviewer has covered more skills and has a high priority to being selected.

The steps of the proposed algorithm are as follows:

a) First step: Fetching the experts'information

At this step, we have fetched information and expertise about each expert that described in the previous files. After fetching the information, regarding the high frequency of existing expertise for any of the reviewers, each reviewer scores have been kept in their part (reviewers have higher scores are selected in the first place). Collected information are available for the algorithm in the next steps. The matrix of Table 1 assumes reviewers D_1 to D_6, and skills x_1, x_2, x_3, x_4, x_5, x_6 available that represents reviewers and skills of each of them. The aim is to sort the reviewers with the most skills. Then, according to the items listed to calculate the score for reviewers, we have obtained it as shown in Table 2. The method of scoring and specifying the reviewers' score has been discussed in the previous sections.

b) Step 2: fetching the required expertise of papers

At this stage, we have fetched details of each paper from the relevant file. Fetched information includes papers and required skills for reviewing each of them. After fetching, this information has been placed within a matrix that one dimension of it contains papers and other one consists of the skills needed for any reviewer. Suppose that in the matrix of Table 3, M_1 to M_5 are papers and x_1, x_2, x_3, x_4, x_5, x_6 are skills required for reviewing papers. To prevent error in the results, we have deleted the skills which there is no reviewer for them, from the list.

c) Step 3: Implementation of the proposed algorithm

In this part, we need an iterative algorithm to examine all papers submitted to review. By using the Knapsack theory based on the bee colony algorithm, we would achieve the best answer to review scientific papers. In this step, we used a cyclic process for selecting reviewers for scientific papers by calling the bee colony algorithm and using the information which has been stored inside the Knapsacks. The process is acceptable for reviewing papers that have the highest scores from the reviewers.In other words, a fewer number of reviewers for reviewing papers is intended. The condition that has been considered in this study is that reviewers cannot simultaneously review more than three papers.

3.2 Implementation

Because of the high volume of users and experts in the social network, in this section, we have collected the expertise of 190 experts using the information listed in their profile as well as articles and previous reviews. Also, we have tested 73 papers in this section that with the study on papers subject, required expertise for reviewing papers has been saved within the file available for the proposed model. In this study, due to simulation, a total of 25 different expertise was used as data for calculations in different algorithms.

The used algorithms are comparative priority-based, and these types of algorithms usually have the high runtime[20]. Therefore, considering the running time for the selection of experts to review scientific papers based on the user's expertise is very important. To achieve less time and increase the efficiency of the algorithm for the calculation of selection of experts to review scientific papers, we should reduce algorithm runtime in the calculation as much as possible.

In this study, we have considered two main factors that may increase the running time of algorithms, and by considering these two factors in the implementation of algorithm, we can achieve good results at an optimal runtime. These two factors are listed below:

1) Priorities of being unique: The results of this study indicate that considering and calculating priorities as well as uniqueness, influence the implementation runtime and thus the algorithm runtime.
2) Increasing the number of experts

In this study, we have used heuristics such as bee colony algorithm. Therefore, by increasing the number of experts, these algorithms can easily and quickly calculate optimal and valid solutions in comparison to the basic algorithms.

By implementing the two algorithms of greedy and the proposed in this paper on the input data set, the proposed approach could obtain the same answers like greedy algorithms in all tested conditions. The difference is the shorter runtime of the proposed algorithm than the greedy algorithms. We have compared times of these algorithms for two states (Table 4).

Given that data and conditions has been considered equal for both algorithms, the evaluation and statistical comparison are the same for both in any of the two variables in the algorithm implementation. Also, in the evaluation of the two algorithms in this study, we have considered the number of required variables according to the type and function of each algorithm, differentlyfrom each other. We have used the two criteria of coverage and confidence in determining the efficiency in this method. These two concepts are described below:

The coverage: If the required skills of an article are shown as n_A, and so, each skill would be A1,..., An_A, and n_r is the number of skills which cover n selected reviewers, we have the following equation (2) for the coverage:

$$\text{Coverage} = \frac{n_r}{n_A} \tag{2}$$

Confidence: The confidence contains calculating the amount of redundancy in the skills of reviewers. Meaning that how many skills they are joint with each other and is repeated in selected different reviewers.

$$\textbf{Confidence} = \frac{\sum_{i=1}^{n_r} \frac{n_{A'i}}{n}}{n_r} \tag{3}$$

If A'1, ..., $A'n_r$ are n_r skills are covered by n reviewers and nA'_i is the number of reviewers that included A'_i skills, the confidence will be obtained from formula (3).

Moreover, we can see that the more is the coverage of an algorithm, the more its efficiency to achieve the ultimate answer. By increasing the number of reviewers, the coverage increases and eventually will be constant and equal to one. The higher confidence leads to achieve more accurate final results of an algorithm and the confidence of algorithm goes close to one. This shows the power of the algorithm to achieve accurate results.

4. Evaluation

For comparison and to obtain the necessary conclusions in this research, we have evaluated the comparison of results in the implementation of each proposed algorithms as well as accurate algorithm and their impact on the calculation of choosing reviewers.

As it can be seen in Figure 2, the comparison between runtime of the two algorithms of greedy and proposed has been shown based on the number of variable papers. In this part, the number of reviewers and expertise has been considered constant.

In Figure 3, the comparison between runtime of the proposed and greedy algorithm with different data concerning the number of experts and equal conditions in papers and the skills required are shown.Which the results show the superiority of the proposed algorithm to accurate algorithm at the time of proposed model implementation.

As it can be seen in Figure 3, the vertical axis shows each algorithm's runtime (in seconds) that graphs with less runtime are related to the proposed algorithm and graphs with more runtime show runtime of the greedy algorithm.Also, in the horizontal part of the graph, execution steps of each algorithm are shown that in this simulation, ten steps of implementations are considered as examples of algorithms different performances.The output from the time of finding the best reviewers (by the best coverage and being special conditions) for papers, shows 70 articles with 30 variable expertise for the variable number of reviewers:

The results of figure 3 indicate that given the same conditions have been considered both regarding the reviewers and their expertise and the content of the papers for both algorithms, the proposed algorithm has less and more efficient runtime than the accurate algorithm in most situations. In the following, the graphs related to the second stage of the algorithms are compared based on the increase in the number of skills and fixing the number of the reviewer in 180. As shown in Figure 4, in the proposed algorithm by fixing the number of reviewers and gradually increasing the number of skills, the runtime would also increase.Also, in Figure 5, we have evaluated the coverage and confidence for both proposed algorithms.

In this section, we compare the graphs and growth of both algorithms and will see that by an increase in the number of reviewers, the amount of coverage for both algorithms will be near 1 and at the end of the list, the amount of coverage will remain constant on 1.Also, we see that by increasing reviewers, the level of confidence will increase.

5. Conclusions

In this study, we have presented a model that designed given the importance of Big Data, for expert's referral to review papers with sufficient expertise and considering two essential criteria of being unique and coverage. We have used the bee colony algorithm for the calculation in designing this model.

After obtaining the information and expertise of experts from social networks, and according to reviewing article and expertise required by reviewers for any of articles, confirmed papers are available to users using the proposed algorithms in less time with higher quality.

This research is seeking a solution to optimize the divestiture process of scientific papers through the selection of experts from social networks, as well as providing an optimal algorithm for studying and selection of judges to review the scientific papers.

References

[1] S.A. Moosavi, M. Jalali, Community detection in online social networks using actions of users, in: 2014 Iran. Conf. Intell. Syst., 2014: pp. 1–7. doi:10.1109/IranianCIS.2014.6802552.

[2] A. El-Korany, Integrated expert recommendation model for online communities, ArXiv Prepr. ArXiv1311.3394. (2013).

[3] M.Z. Shafiq, M.U. Ilyas, A.X. Liu, H. Radha, Identifying leaders and followers in online social networks, IEEE J. Sel. Areas Commun. 31 (2013) 618–628.

[4] B. bin Baharudin, A case study on travel information from social network—Focus in Facebook and blogs in Malaysia, in: Comput. Inf. Sci. (ICCOINS), 2014 Int. Conf., IEEE, 2014: pp. 1–6.

[5] T. Lappas, K. Liu, E. Terzi, Finding a team of experts in social networks, in: Proc. 15th ACM SIGKDD Int. Conf. Knowl. Discov. Data Min., ACM, 2009: pp. 467–476.

[6] E. Pournoor, J. Rezaenoor, A New Expert Finding Model Based on Term Correlation Matrix, Iran. J. Inf. Process. Manag. 30 (2015) 1147–1171.

[7] K. Balog, L. Azzopardi, M. de Rijke, A language modeling framework for expert finding, Inf. Process. Manag. 45 (2009) 1–19.

[8] M. Neshati, S.H. Hashemi, H. Beigy, Expertise finding in bibliographic network: Topic dominance learning approach, IEEE Trans. Cybern. 44 (2014) 2646–2657.

[9] M. Karimzadehgan, C. Zhai, Integer linear programming for constrained multi-aspect committee review assignment, Inf. Process. Manag. 48 (2012) 725–740.

[10] M. Cha, H. Haddadi, F. Benevenuto, P.K. Gummadi, Measuring user influence in twitter: The million follower fallacy, Icwsm. 10 (2010) 30.

[11] F. Bodendorf, C. Kaiser, Detecting opinion leaders and trends in online social networks, in: Proc. 2nd ACM Work. Soc. Web Search Min., ACM, 2009: pp. 65–68.

[12] H. Deng, I. King, M.R. Lyu, Enhanced models for expertise retrieval using community-aware strategies, IEEE Trans. Syst. Man, Cybern. Part B. 42 (2012) 93–106.

[13] S.H. Hashemi, M. Neshati, H. Beigy, Expertise retrieval in bibliographic network: a topic dominance learning approach, in: Proc. 22nd ACM Int. Conf. Conf. Inf. Knowl. Manag., ACM, 2013: pp. 1117–1126.

[14] H. Yin, B. Cui, Y. Huang, Finding a wise group of experts in social networks, in: Int. Conf. Adv. Data Min. Appl., Springer, 2011: pp. 381–394.

[15] M. Neshati, E. Asgari, D. Hiemstra, H. Beigy, A joint classification method to integrate scientific and social networks, in: Eur. Conf. Inf. Retr., Springer, 2013: pp. 122–133.

[16] M. Neshati, H. Beigy, D. Hiemstra, Expert group formation using facility location analysis, Inf. Process. Manag. 50 (2014) 361–383.

[17] M. Neshati, H. Beigy, D. Hiemstra, Multi-aspect group formation using facility location analysis, in: Proc. Seventeenth Australas. Doc. Comput. Symp., ACM, 2012: pp. 62–71.

[18] E. Smirnova, A model for expert finding in social networks, in: Proc. 34th Int. ACM SIGIR Conf. Res. Dev. Inf. Retr., ACM, 2011: pp. 1191–1192.

[19] W. Tang, J. Tang, T. Lei, C. Tan, B. Gao, T. Li, On optimization of expertise matching with various constraints, Neurocomputing. 76 (2012) 71–83.

[20] W. Li, Z. Ye, M. Xin, Q. Jin, Social recommendation

based on trust and influence in SNS environments, Multimed. Tools Appl. 76 (2017) 11585–11602.

Table captions:

Table 1: Reviewers and their skills
Table 2: Calculating the reviewers score
Table 3: Papers and skills required
Table 4: Comparing the runtimes of the proposed algorithm with the greedy algorithms based on the number of the variables

Figure captions:
Figure 1: Conceptual model and implementation parts of the research
Figure 2: Time to find reviewers for articles based on the number of variable papers
Figure 3: time to find the best group of experts for 70 articles with 30 different expertise
Figure 4: Run time of the proposed algorithm along with greedy algorithm based on the number of skills
Figure 5: Amount of coverage and confidence of the two algorithms based on the number judges for an article

Table 1: Reviewers and their skills

	x_1	x_2	x_3	x_4	x_5	x_6
D_1	0	1	0	1	0	1
D_2	0	0	1	0	0	0
D_3	1	0	1	0	0	0
D_4	0	0	0	0	1	1
D_5	1	1	0	0	0	0
D_6	0	0	1	1	0	0

Table 2: Calculating the reviewers score

	D_1	D_2	D_3	D_4	D_5	D_6
Being special	0/01	0/001	0/01	0/1	0/01	0/01
Coverage	3	1	2	2	2	2
Final score	0/03	0/001	0/02	0/2	0/02	0/02

Table 3: Papers and skills required

	X_1	X_2	X_3	X_4	X_5	X_6
M1	1	0	1	1	0	0
M 2	0	1	1	0	1	0
M3	1	0	1	1	0	1
M4	0	0	0	0	1	1
M5	1	1	0	1	0	0

Table 4: Comparing the runtimes of the proposed algorithm with the greedy algorithms based on the number of the variables

Greedy algorithm (s)	The proposed algorithm(s)	Number of skills	The Greedy algorithm(s)	The proposed algorithm(s)	Number of reviewers	The Greedy algorithm(s)	The proposed algorithm(s)	Number of Articles
15	30	5	10	20	10	48	80	10
38	42	10	22	40	30	143	112	50
82	73	15	47	55	60	210	120	70
146	103	20	75	78	80	263	138	85
210	120	25	120	95	120	320	148	110
312	147	30	156	110	150	380	164	140
411	158	35	210	120	180	456	176	170
508	162	40	393	140	300	563	196	250
617	169	45	582	160	500	754	240	400
709	171	50	930	165	800	890	262	450

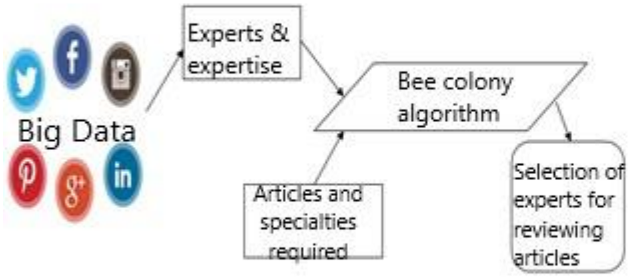

Figure 1: Conceptual model and implementation parts of the research

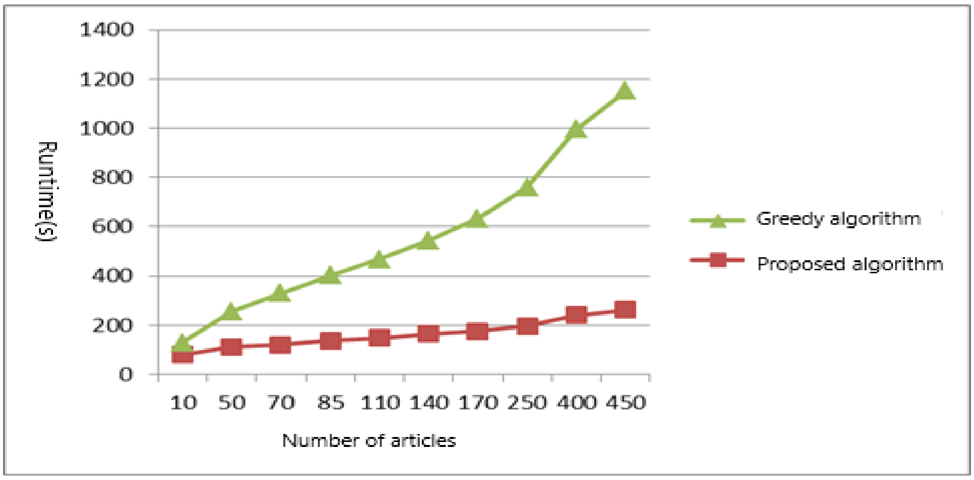

Figure 2: Time to find reviewers for articles based on the number of variable papers

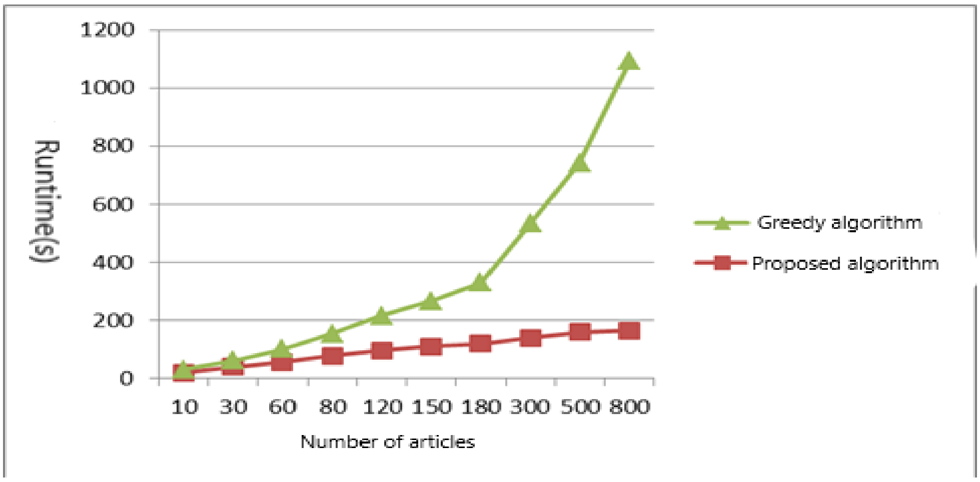

Figure 3: Time to find the best group of experts for 70 articles with 30 different expertise

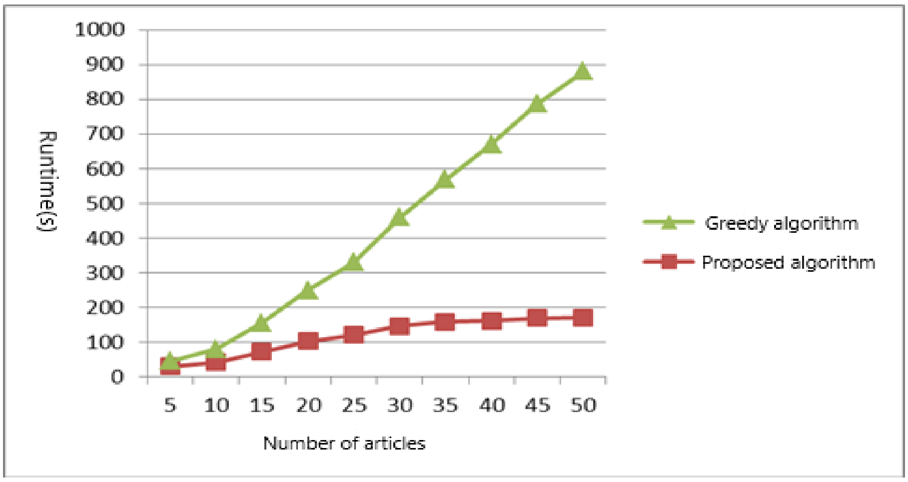

Figure 4: Run time of the proposed algorithm along with greedy algorithm based on the number of skills

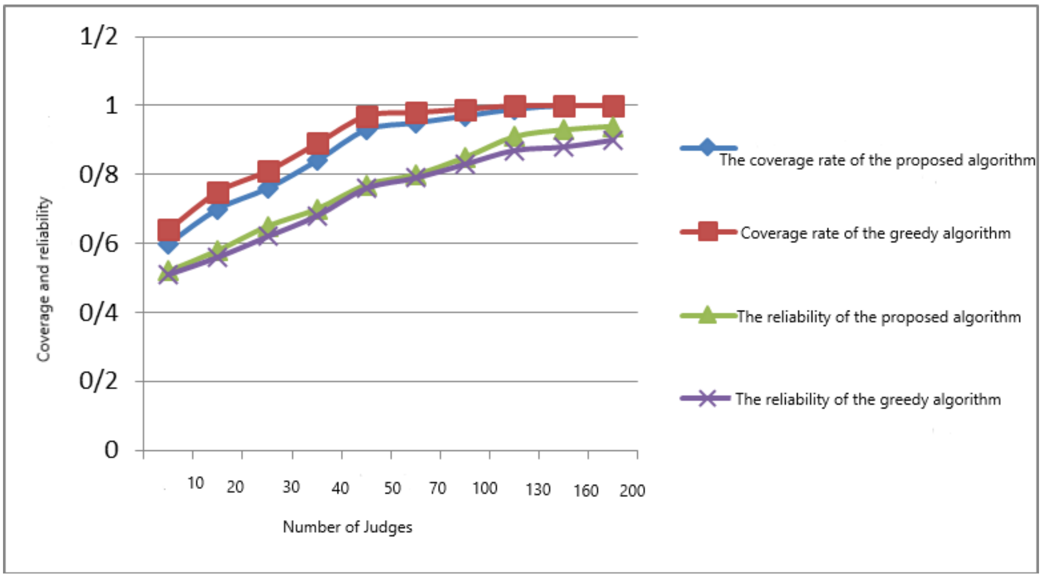

Figure 5: Amount of coverage and confidence of the two algorithms based on the number judges for an article