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Measuring journal performance for multidisciplinary research: An efficiency perspective

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ABSTRACT

One of the flaws of the journal impact factor (IF) is that it cannot be used to compare journals from different fields or multidisciplinary journals because the IF differs significantly across research fields. This study proposes a new measure of journal performance that captures field-different citation characteristics. We view journal performance from the perspective of the efficiency of a journal's citation generation process. Together with the conventional variables used in calculating the IF, the number of articles as an input and the number of total citations as an output, we additionally consider the two field-different factors, citation density and citation dynamics, as inputs. We also separately capture the contribution of external citations and self-citations and incorporate their relative importance in measuring journal performance. To accommodate multiple inputs and outputs whose relationships are unknown, this study employs data envelopment analysis (DEA), a multi-factor productivity model for measuring the relative efficiency of decision-making units without any assumption of a production function. The resulting efficiency score, called DEA-IF, can then be used for the comparative evaluation of multidisciplinary journals' performance. A case study example of industrial engineering journals is provided to illustrate how to measure DEA-IF and its usefulness.

1. Introduction

Measuring journal performance has been a matter of concern for science policy makers as well as various stakeholders in academia, such as librarians, researchers, and editors. Undoubtedly, the most commonly used measure of journal performance or quality is the journal impact factor (IF), published annually in the Journal Citation Reports (JCR) produced by Thomson Reuters. The use of the IF as an indicator of journal quality is underlain by the assumption that citation frequency accurately measures a journal's importance to its end users (Saha, Saint, & Christakis, 2003). Due to its comprehensibility, robustness, simplicity, and availability, the IF has been increasingly popular and widely used for various purposes (Franceschet, 2010): librarians make subscription decisions under limited funds by referring to journals' IFs; researchers are eager to submit their work to journals with a high IF; editors and publishers of journals with a favorable IF employ it as a means of advertising their journals; universities adopt the IF as a criterion for the promotion and tenure decisions of their faculty members; and governmental funding boards judge scientists for grant allocation based on the IF (Cameron, 2005; Dong, Loh, & Mondry, 2005; Sombatsompop, Markpin, & Premkamolnetr, 2004).

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However, the deficiencies of the IF have also been extensively reported in previous studies (Amin & Mabe, 2000; Archambault & Larivière, 2009; Bordons, Fernández, & Gomez, 2002; Cameron, 2005; Dong et al., 2005; Glänzel & Moed, 2002; Ha, Tan, & Soo, 2006; Seglen, 1997; van Leeuwen & Moed, 2002). The use of the IF has been criticized from four points of view: representativeness, coverage, operational definition, and field-dependency. Firstly, the IF of a journal is not statistically representative of individual articles published in the journal. Seglen (1997) found that the most cited 15% of the articles account for 50% of the citations, and the half of the articles account for 90% of the citations. Since the IF only measures average article citation rates, it cannot be used as a measure of individual articles. The second issue is associated with the narrow coverage of the database used to calculate the IF. Web of Knowledge provided by Thomson Reuters currently covers about 12,000 journals which is less than 10% of all journals throughout the world (estimated as 126,000 in Seglen (1997)). The database has also a preference for English language American journals. Books are not even included as sources in the database even though a substantial fraction of scientific output is published in the form of books. Thirdly, the IF has some technical problems with its operational definition. The IF of a journal is defined as the average number of citations received per paper published in the journal in a given year during the two preceding years (Garfield, 1955). One of the problems is the article types included in the numerator and the denominator are not consistent. Only citable items such as articles, notes, and reviews are included in the denominator while the numerator contains citations to all types of publications including editorials, letters, and meeting abstracts. The composition of types of articles also influences on the IF since reviews are more likely to be cited than original research papers. Inclusion of self-citations in the numerator is also controversial, and this will be further discussed later. Another important operational issue is the two-year citation window. A strong temporal bias may occur under such a short time frame because faster publication will likely result in higher IFs. A field with short publication lags enjoys high portion of citations to recent articles, which leads to higher IFs. The short window is one of the main reasons causing the significant field-to-field variation of the IF, combined with different citation dynamics which will be discussed right after.

The fourth issue is field-dependency of the IF, which is exactly what this study seeks to resolve. The level of the IF significantly differs across research fields and subject areas. The variation is mainly attributed to different citation densities and citation dynamics across fields (Dong et al., 2005; Seglen, 1997). Citation density—the mean number of references per article—varies considerably from field to field. It is well known that the IF is a function of citation density in a research field; thus, a field that has higher citation density is likely to have a higher IF (Garfield, 2006). Articles in rapidly growing fields such as biochemistry tend to cite a lot more recent references than more durable fields such as mathematics. This is known as citation dynamics, and it has a significant effect on IF because citations within only two years are counted in calculating the IF. A large portion of citations are captured in IFs in highly dynamic fields, while durable fields have a smaller fraction of short-term citations and hence have lower IFs (Dong et al., 2005; Seglen, 1997; Sombatsompop et al., 2004).

For these reasons, it is not generally recommended that the IF be used to compare journals from different fields. Nonetheless, the misuse of the IF in evaluating researchers and research institutes in different fields has been increasingly frequently observed (Pudovkin & Garfield, 2004). In an effort to make cross-field comparisons possible, some normalization procedures have been developed to accommodate the variation in IFs across fields (Marshakova-Shaikevich, 1996; Owlia, Vasei, Goliaei, & Nassiri, 2011; Pudovkin & Garfield, 2004; Ramírez, García, & Del Río, 2000; Sen, 1992). Those normalization procedures are only focused on calculating the relative positions of journals within each subject category, rather than explicitly considering different citation densities and citation dynamics across categories (Dorta-González & Dorta-González, 2013). Consequently, such normalization approaches cannot be applied to a comparative evaluation of multidisciplinary journals although citation analysis is the most common technique for measuring output of multidisciplinary research (Wagner et al., 2011). Many multidisciplinary journals are affiliated with multiple categories and thus a normalized procedure produces different scores for a single journal. What is worse is that some categories in JCR are multidisciplinary themselves. Even if some journals are classified into the same category, their IFs are highly dependent on the citation characteristics of the disciplines with which each journal is connected. Therefore, the requisite for measuring the performance of multidisciplinary journals is to explicitly capture different citation densities and citation dynamics across fields.

The tenet of this paper is that an efficiency-based measure can be a good remedy for measuring the performance of multidisciplinary journals. Basically, the IF is a productivity measure defined as the ratio of outputs (the number of citations) to inputs (the number of articles). In other words, the IF can be viewed as an indicator of how productive journals' citation generation processes are. However, the number of articles published in a journal is not the only input of the journal's scientific dissemination process. Our perspective is that the number of references to be cited and the time lag between publication and subsequent citation are also critical inputs to produce citations; thus, we explicitly consider the two factors that influence the IF—the citation density and citation dynamics of the fields to which a journal is related—as inputs of the knowledge dissemination of the journal. To accommodate multiple inputs in measuring productivity with an unknown production function, this study employs data envelopment analysis (DEA), which is a multi-factor productivity model for measuring the relative efficiency of decision making units (DMUs) without any assumption of the functional form of a production function. By incorporating the two field-dependent factors, citation density and citation dynamics, as well as the number of articles as inputs of the process of DMUs (journals), DEA produces their efficiency scores, called DEA-IF, as a measure of journal performance. The obtained DEA-IF can be used for comparative evaluation of multidisciplinary journals' performance because it mirrors different citation-related characteristics of the various fields in which each journal is involved.

Another important issue in calculating the IF is the inclusion of journal self-citation. There has been a long debate over whether to include journal self-citations (Archambault & Larivière, 2009). Since self-citation substantially influences the total level of a journal's citation and plays an important role in forming the IF (Falagas & Alexiou, 2008), some editors are tempted to manipulate the IF by urging authors to cite articles published in their journal (Agrawal, 2005; Smith, 1997). Nonetheless, a non-gratuitous journal self-citation is also valuable because it indicates whether a contribution is well placed within its discipline (Vanclay, 2013). A high volume of self-citation is not unusual or unwarranted in leading journals due to the uniqueness or novelty of their subject matter as well as the consistently high quality of the papers that they publish (McVeigh, 2002). Thus, JCR still includes journal self-citations in calculating the IF, although it also provides an additional indicator, the IF without self-citations. There is no universal agreement on whether to include or exclude journal self-citations and how much more or less important self-citations are than external citations. To cope with this problem, we utilize the weights restriction technique in DEA. As output variables, total citations are decomposed into self-citations and external citations. Imposing restrictions on the proportion of contributions of the two types of citations to IFs then enables evaluators to flexibly mirror their own judgment of their relative importance.

The remainder of this paper is organized as follows. Section 2 reviews the use of DEA for research evaluation and the DEA models used in this study. The model for measuring DEA-IF are explained in Section 3 and an example of industrial engineering journals is presented in Section 4. The paper ends with conclusions and directions for future research in Section 5.

2. DEA for measuring research performance

DEA is a non-parametric approach to measuring the relative efficiency of DMUs with multiple factors (Cooper, Seiford, & Tone, 2007). The relative efficiency of a DMU is measured by estimating the ratio of weighted outputs to weighted inputs and comparing it with other DMUs. Recent years have seen a huge increase in the use of DEA for measuring R&D performance because it has the following attractive features (Lee, Park, & Choi, 2009; Wang & Huang, 2007). First, DEA is capable of handling multiple inputs and outputs in efficiency evaluation. R&D activities typically involve multiple inputs and outputs, which cannot be easily dealt with in the standard parametric methods. DEA enables various types of inputs and outputs of R&D activities to be considered in performance evaluation. Second, DEA can be utilized for cases where the relationships between inputs and outputs are unknown. Since DEA does not require any assumptions about the functional form of a production function, it fits R&D activities whose production functions cannot be specified. Third, DEA is useful for situations in which prior information on preferences about variables does not exist. This is exactly the context of R&D performance evaluation in which there is no universally agreed-upon view on the importance of R&D inputs and outputs. DEA solves this problem by automatically deriving the weights that represent a relative value system for each DMU.

Due to such merits, DEA has enjoyed a variety of applications as a tool for R&D performance evaluation at various levels, such as nations (Lee & Park, 2005; Sharma & Thomas, 2008; Wang & Huang, 2007), research institutes (Liu & Lu, 2010), programs (Lee et al., 2009), and projects (Eilat, Golany, & Shtub, 2006; Hsu & Hsueh, 2009). Research performance in academia has also frequently been studied with different levels of DMUs, such as universities (Cherchye & Abeele, 2005; Feng, Lu, & Bi, 2004), departments across universities (Abramo, D'Angelo, & Pugini, 2008; Johnes & Johnes, 1993), research programs at different universities (Groot & Garcia-Valderrama, 2006), and research units within a university (Korhonen, Tainio, & Wallenius, 2001). Those studies intended to measure research efficiency in terms of the scientific article production process, mainly based on the number of papers published as outputs. No studies have been conducted to measure journals' efficiency in the citation generation process for knowledge dissemination. One attempt to measure journals' efficiency was made by Petridis, Malesios, Arabatzis, and Thanassoulis (2013). They utilized DEA for the efficiency analysis of forestry journals based on two inputs (frequency of publication of a journal within a year and articles published per year) and three types of journal performance measures as outputs (eigenfactor score, h-index, and 5-year impact factor). However, the purpose of using DEA in their study lies in producing a single composite indicator by aggregating different existing measures of journal performance, rather than developing a new efficiency-based measure of journal performance for the comparison of multidisciplinary journals.

Various DEA models are available for the measurement of research performance. The first DEA model proposed by Charnes, Cooper, and Rhodes (1978), called CCR, assumes that production exhibits constant returns to scale. Banker, Charnes, and Cooper (1984) extended the CCR model to the BCC model which allows variable returns to scale. Since there is no evidence that the citation generation process of a journal exhibits constant returns to scale, we adopt the BCC model in this study. DEA models are also distinguished by their objectives: to maximize outputs (output-oriented) or to minimize inputs (input-oriented). It is implicitly assumed that the objective of the citation generation process lies in increasing outputs (citations) rather than decreasing inputs (e.g. articles published). Therefore, this study adopts the output-oriented model. The output-oriented BCC model in the multiplier form is formulated as

$$
\begin{aligned}
&\min \textstyle\sum_{i=1}^{m} v_i x_{ik} - z \\
&s.t. \textstyle\sum_{r=1}^{s} u_r y_{rk} = 1, \\
&\textstyle\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - z \geq 0 \, (j = 1, \ldots, n), \\
&\quad v_i \geq 0, (i = 1, \ldots, m), \\
&\quad u_r \geq 0, (r = 1, \ldots, s), \\
&\quad z : free
\end{aligned}
\tag{1}
$$

where x_{ij} is the amount of the ith input of DMU j, y_{ij} is the amount of the rth output DMU j, v_j is the weight given to the ith input, u_r is the weight given to the rth output, and k is the DMU being measured. The only difference between the CCR and BCC model is the presence of z, which is the dual variable associated with the convexity condition in the envelopment form.

Solving the linear programming models for all DMUs assigns a best set of weights to each DMU, where "best" means that the resulting efficiency score is maximized under the given data. However, if prior knowledge or accepted views exist, this weight flexibility in DEA leads to the production of unrealistic efficiency scores (Allen, Athanassopoulos, Dyson, & Thanassoulis, 1997). For instance, the inclusion of self-citations in measuring journal performance is controversial, as mentioned above, but it is obvious that external citations are more important than self-citations. Thus, the contribution of external citations to a journal performance measure should be higher than that of self-citations. When this is the case, restrictions need to be placed to mirror preference in a real world. One of the most widely used techniques for weight restriction is the assurance regions (AR) model proposed by Thompson, Langemeier, Lee, Lee, and Thrall (1990). The AR model imposes restrictions on the upper and lower bounds of a ratio of the weights of two inputs/outputs (Type 1) or of one input and one output (Type 2). Rather than restricting the actual weights, Wong and Beasley (1990) proposed the use of restricting virtual inputs/outputs, which is later called the AR global (ARG) model by Cooper et al. (2007). In the ARG model, the proportion of the total virtual input of DMU j devoted to input i, i.e. the importance attached to input i, is restricted to range between [L_i, U_i]. The restriction on the virtual input i takes the form,

$$L_i \leq \frac{v_i x_{ij}}{\sum_{i=1}^{m} v_i x_{ij}} \leq U_i \tag{2}$$

where $\sum_{i=1}^{m} v_i x_{ij}$ represents the total virtual input of DMU j. A similar restriction can be imposed on the virtual outputs. Since the ARG model is capable of directly reflecting the relative importance of variables, it is more intuitively appealing than the traditional AR model (Cooper et al., 2007), particularly in situations where the units of variables are variant. This study also employs the ARG model to mirror the relative importance between variables.

3. Model

The first step in measuring journal performance with DEA is to select relevant input and output variables. As a measure of journal performance, the DEA-IF indicates the efficiency of journals' scientific dissemination process by inducing citations. As in the case of the original IF, the primary input for the process is the number of articles published in a journal. The higher the number of articles, the more chances the journal has to be cited. We also consider additional inputs contributing to the journals' citation generation process. As mentioned earlier, there is a consensus that the citation density and citation dynamics of a field are key factors that influence IF (Cameron, 2005; Dong et al., 2005; Garfield, 2006). Higher citation densities and faster citation dynamics of the fields to which a journal is relevant are likely to induce more citations and thus they are selected as inputs. One may also consider the size of a field, that is, the number of journals/articles/researchers in the field, as an influencing factor. Some studies insist that the bigger the size of a field, the greater the overall IF for the discipline (Amin & Mabe, 2000; Cameron, 2005; Jemec, 2001). On the other hand, Garfield (2006) claimed that the number of authors or articles does not affect the IF because it is expressed as a ratio, though it will increase the number of "super-cited" papers. Althouse, West, Bergstrom, and Bergstrom (2009) also empirically demonstrated that cross-filed differences in net size have little influence on the IF. Since the size matter is still controversial, we do not consider the size of a field in this study. In sum, we measure the DEA-IF with three inputs: number of articles, citation density, and citation dynamics. When it comes to outputs, the number of total citations, which is also the numerator of the original IF, is also chosen. In addition, we divide the total citations of a journal into external citations from other journals and self-citations by the journal in order to mirror the relative importance between them in measuring the DEA-IF.

The selected variables and their operational definitions are given in Table 1. To compare DEA-IF with the original IF, the two-year citation window is also adopted. The operational definitions of the number of articles and all three output variables are quite straightforward and their values for each journal are directly available in JCR. The two input variables, citation density and citation dynamics, are measured at the category level. The citation density of a category is defined as the

Table 1
DEA variables and operational definitions.

Type	Variable	Operational definition
Input	Articles (I1)	The number of citable items published in a journal in the two preceding years
	Citation density (I2)	The average number of references per items of the categories with which a journal is affiliated in the two preceding years
	Citation dynamics (I3)	10 – The average cited half-life of the categories with which a journal is affiliated in a given year
Output	Total citations (O1)	The number of total citations in a given year to items published in a journal in the two preceding years
	External citations (O2)	The number of external citations in a given year to items published in a journal in the two preceding years
	Self-citations (O3)	The number of self-citations in a given year to items published in a journal in the two preceding years

Table 2
Model specification.

Model	Variables included						Weight restriction	
	Articles (I1)	Citation density (I2)	Citation dynamics (I3)	Total citations (O1)	External citations (O2)	Self-citations (O3)	Input	Output
BCC1	○	○		○				
BCC2	○		○	○				
BCC3	○	○	○	○				
BCC4	○	○	○		○	○		
ARG1	○	○	○		○	○	○	
ARG2	○	○	○		○	○		○
ARG3	○	○	○		○	○	○	○

ratio of the total number of references in the category to its total number of citable items. The citation density of a journal is then obtained by averaging the values of citation density of the categories with which the journal is affiliated. Citation dynamics are measured by borrowing a JCR indicator of the longevity of articles, the cited half-life. The cited half-life of a journal/category is defined as the number of publication years from the current year that accounts for 50% of current citations received. In other words, half of the cited articles of a journal/category were published more recently than the cited half-life, which indicates that the higher the cited half-life, the less dynamic the journal/field. Thus, it is necessary to transform the values of the cited half-life in a way by which more dynamic fields have higher values than less dynamic ones. Since the maximum value of the cited half-life is restricted to 10 years, we define the citation dynamics of a journal as the difference between 10 years and the average cited half-life of the categories with which a journal is affiliated.

It should be noted that citation density and citation dynamics can also be measured at an individual journal level. The reason for taking averages of related fields, rather than using the values of each journal, is that the citation density and cited half-life of a journal are not inputs but outcomes of the journal's citation generation process because they are measured based on the citations of the journal in the current year, which were already influenced by different citation-related characteristics of different related fields. To explicitly consider field-different characteristics of multidisciplinary journals as inputs of a journal's scientific dissemination process, it makes sense to take the citation densities and citation dynamics of fields in which each journal is involved. One should also note that we take the cited half-life of the current year, while citation density is measured for the two preceding years. This is because the cited half-life of a given year is measured from the citations received in the two preceding years.

To examine the effect of the inclusion of additional variables and to mirror the relative importance of variables, we measure the DEA-IF with multiple models. Table 2 presents the specifications of seven DEA-IF models. As mentioned in Section 2, the output-oriented BCC model is employed as a basic DEA model, and four variants of the BCC model are specified by what variables are included. Based on the basic composition of articles as an input and total citations as an output, which is the same as the original IF model, the BCC1 and BCC2 models additionally include citation density and citation dynamics, respectively, and both are included in the BCC3 model. The BCC4 model divides total citations into self-citations and external citations with all three types of inputs. We also employ the ARG model to consider the preference in the real world. The variable compositions of the ARG models are the same as the BCC4 model, but they are specified by which types of variables are restricted in their weights: inputs in ARG1, outputs in ARG2, and both in ARG3. Comparing the DEA-IF scores of different specifications as well as with the original IF will provide fruitful implications for the measurement of journal performance from the perspective of efficiency.

4. Example: industrial engineering journals

The workings of the DEA-IF model are explained with the help of a case study example of industrial engineering. Industrial engineering is one of the established engineering disciplines, but it is multidisciplinary in nature (Elsayed, 1999). Starting with scientific management in the 1930s, industrial engineering has continued to expand its boundaries by embracing other science and engineering disciplines, such as statistics, ergonomics, manufacturing engineering, operations research, and computer science. In the meantime, it has also expanded its range into social sciences such as psychology, business, and economics.

The multidisciplinary nature of industrial engineering can be easily seen in the JCR. Forty-three journals are currently categorized into *Engineering, Industrial* (ENG-IND) in the SCI edition of the JCR. The full journal titles and ISSN numbers are given in Appendix A. It is found that most of the industrial engineering journals are also included in other categories, as shown in Table 3. The 17 subject categories of the Social Science Citation Index (SSCI) as well as the SCI are found to be related with at least one journal of industrial engineering, which demonstrates that it is necessary to consider field-different characteristics in measuring journal performance. It is not surprising that about 40% of industrial engineering journals are simultaneously categorized into *Operations Research & Management Science*, as it is one of the core parts of industrial engineering. Other relevant disciplines are *Management*, *Business*, *Computer Science*, *Statistics & Probability*, and *Psychology*. It has been shown that the three categories of SSCI (*Business*, *Management*, and *Applied Psychology*) have higher citation densities and cited

Table 3
Industrial engineering-related categories and their citation characteristics.

Category	Edition	Number of affiliated IE journals	Citation density	Cited half-life
Automation & Control Systems (A&CS)	SCI	1	27.2	7.1
Behavioral Sciences (BS)	SCI	1	56.4	8.0
Business (BUS)	SSCI	4	57.5	10.0
Computer Science, Interdisciplinary Applications (CS-IA)	SCI	4	32.6	6.9
Construction & Building Technology (C&BT)	SCI	1	25.3	7.3
Engineering, Civil (ENG-CIV)	SCI	2	28.3	6.3
Engineering, Electrical & Electronic (ENG-EE)	SCI	1	22.7	6.8
Engineering, Industrial	SCI	43	34.1	7.8
Engineering, Manufacturing (ENG-MAN)	SCI	8	28.4	6.8
Engineering, Multidisciplinary (ENG-MUL)	SCI	4	26.4	7.6
Management (MGT)	SSCI	5	58.3	10.0
Materials Science, Multidisciplinary (MS-M)	SCI	1	32.2	5.2
Multidisciplinary Sciences (MS)	SCI	2	35.5	8.8
Operations Research & Management Science (OR&MS)	SCI	18	31.6	8.6
Psychology (PSY)	SCI	3	49.9	10.0
Psychology, Applied (PSY-A)	SSCI	1	54.1	9.9
Robotics (ROB)	SCI	1	30.0	6.8
Statistics & Probability (S&P)	SCI	4	26.2	10.0

Table 4
Industrial engineering journals in JCR.

Journal	IF		Affiliated categories			
	Score	Rank	Number	Names (excluding ENG-IND)		
APPL ERGON	1.428	12	1			
CIRP ANN-MANUF TECHN	1.708	8	2	ENG-MAN		
COMPUT IND ENG	1.589	9	2	CS-IA		
COMPUT OPER RES	1.720	7	3	CS-IA	OR&MS	
EMJ-ENG MANAG J	0.089	42	1			
ENG ECON	0.382	36	2	OR&MS		
ERGONOMICS	1.409	13	3	PSY	PSY-A	
EUR J IND ENG	0.413	34	2	OR&MS		
HUM FACTORS	1.187	17	3	BS	PSY	
IEEE IND APPL MAG	0.640	30	2	ENG-EE		
IEEE T ENG MANAGE	0.958	20	3	BUS	MGT	
IEEE T IND INFORM	2.990	2	3	A&CS	CS-IA	
IIE TRANS	0.856	22	2	OR&MS		
IND ENG	0.059	43	1			
IND MANAGE DATA SYST	1.472	11	2	CS-IA		
IND ROBOT	0.603	32	2	ROB		
INT J IND ENG-THEORY	0.154	40	2	ENG-MAN		
INT J IND ERGONOM	1.260	15	1			
INT J PROD ECON	1.760	6	3	ENG-MAN	OR&MS	
INT J PROD RES	1.115	18	3	ENG-MAN	OR&MS	
ISSUES SCI TECHNOL	0.652	28	3	ENG-MUL	MS	
J CONSTR ENG M ASCE	0.818	23	3	C&BT	ENG-CIV	
J ENG TECHNOL MANAGE	1.032	19	4	BUS	MGT	OR&MS
J MANAGE ENG	0.787	24	2	ENG-CIV		
J MANUF SYST	0.639	31	3	ENG-MAN	OR&MS	
J MATER PROCESS TECH	1.783	4	3	ENG-MAN	MS-M	
J PROD INNOVAT MANAG	2.109	3	3	BUS	MGT	
J QUAL TECHNOL	1.564	10	3	OR&MS	S&P	
P I MECH ENG O-J RIS	0.393	35	3	ENG-MUL	OR&MS	
PROBAB ENG INFORM SC	0.642	29	3	OR&MS	S&P	
PROD PLAN CONTROL	0.725	26	3	ENG-MAN	OR&MS	
QUAL ENG	0.745	25	2	S&P		
QUAL RELIAB ENG INT	0.700	27	3	ENG-MUL	OR&MS	
QUAL TECHNOL QUANT M	0.276	37	3	OR&MS	S&P	
R&D MAG	0.167	39	2	MS		
RELIAB ENG SYST SAFE	1.770	5	2	OR&MS		
RES ENG DES	1.243	16	3	ENG-MAN	ENG-MUL	
RES TECHNOL MANAGE	0.885	21	3	BUS	MGT	
S AFR J IND ENG	0.215	38	1			
SAFETY SCI	1.402	14	2	OR&MS		
SYSTEMS ENG	0.420	33	2	OR&MS		
TECHNOVATION	3.287	1	3	MGT	OR&MS	
TRAV HUMAIN	0.143	41	2	PSY		

Table 5
DEA-IF in the BCC models.

Journal	BCC1			BCC2			BCC3			BCC4		
	Score	Rank	Diff IF	Score	Rank	Diff IF	Score	Rank	Diff IF	Score	Rank	Diff BCC3
APPL ERGON	0.6263	18	−6	0.5816	17	−5	0.6462	22	−10	0.6464	22	0
CIRP ANN-MANUF TECHN	0.8153	14	−6	0.7329	13	−5	0.8292	18	−10	0.8685	18	0
COMPUT IND ENG	0.8165	13	−4	0.7936	12	−3	0.8219	19	−10	0.8323	19	0
COMPUT OPER RES	0.8804	11	−4	0.8486	9	−2	0.9278	17	−10	0.9335	17	0
EMJ-ENG MANAG J	0.0493	42	0	0.0455	42	0	0.0493	42	0	0.0763	42	0
ENG ECON	0.9994	8	28	0.2954	26	10	0.9997	12	24	0.9998	12	0
ERGONOMICS	0.5774	20	−7	1.0000	1	12	1.0000	1	12	1.0000	1	0
EUR J IND ENG	0.2254	33	1	0.2065	33	1	0.2609	33	1	0.3631	33	0
HUM FACTORS	0.3780	24	−7	0.3780	23	−6	0.3780	29	−12	0.5692	25	4
IEEE IND APPL MAG	0.9996	7	23	0.2159	32	−2	0.9996	14	16	0.9997	14	0
IEEE T ENG MANAGE	0.3160	28	−8	0.5126	18	2	0.5126	25	−5	0.5543	26	−1
IEEE T IND INFORM	1.0000	1	1	0.9652	7	−5	1.0000	1	1	1.0000	1	0
IIE TRANS	0.3270	27	−5	0.2838	27	−5	0.3874	28	−6	0.4853	28	0
IND ENG	0.0210	43	0	0.0185	43	0	0.0216	43	0	0.0331	43	0
IND MANAGE DATA SYST	0.5442	21	−10	0.4737	19	−8	0.5442	23	−12	0.6012	24	−1
IND ROBOT	0.2096	34	−2	0.1882	35	−3	0.2096	35	−3	0.2696	35	0
INT J IND ENG-THEORY	0.0630	41	−1	0.0595	41	−1	0.0630	41	−1	0.0817	41	0
INT J IND ERGONOM	0.5168	22	−7	0.4707	20	−5	0.5324	24	−9	0.6107	23	1
INT J PROD ECON	0.9346	10	−4	0.8953	8	−2	1.0000	1	5	1.0000	1	0
INT J PROD RES	0.6089	19	−1	0.6455	15	3	0.7912	20	−2	0.8294	20	0
ISSUES SCI TECHNOL	0.2565	31	−3	0.2446	28	0	0.2741	32	−4	0.4262	31	1
J CONSTR ENG M ASCE	0.9996	6	17	0.3446	24	−1	0.9996	13	10	0.9997	13	0
J ENG TECHNOL MANAGE	1.0000	1	18	1.0000	1	18	1.0000	1	18	1.0000	1	0
J MANAGE ENG	0.4239	23	1	0.3854	22	2	0.4239	27	−3	0.4818	29	−2
J MANUF SYST	0.9987	9	22	0.4423	21	10	0.9995	15	16	0.9996	15	0
J MATER PROCESS TECH	1.0000	1	3	1.0000	1	3	1.0000	1	3	1.0000	1	0
J PROD INNOVAT MANAG	0.6667	17	−14	1.0000	1	2	1.0000	1	2	1.0000	1	0
J QUAL TECHNOL	0.7265	15	−5	0.6719	14	−4	1.0000	1	9	1.0000	1	0
P I MECH ENG O-J RIS	0.1688	36	−1	0.1579	36	−1	0.1869	36	−1	0.2161	37	−1
PROBAB ENG INFORM SC	0.2593	30	−1	0.2443	29	0	0.4369	26	3	0.4377	30	−4
PROD PLAN CONTROL	0.2492	32	−6	0.2297	30	−4	0.2845	31	−5	0.3909	32	−1
QUAL ENG	0.3480	26	−1	0.3203	25	0	0.9998	11	14	0.9999	11	0
QUAL RELIAB ENG INT	0.3136	29	−2	0.2221	31	−4	0.3607	30	−3	0.5274	27	3
QUAL TECHNOL QUANT M	0.1228	37	0	0.1143	37	0	0.1860	37	0	0.2678	36	1
R&D MAG	0.1008	39	0	0.0921	39	0	0.1151	39	0	0.1780	38	1
RELIAB ENG SYST SAFE	0.8484	12	−7	0.7964	11	−6	0.9496	16	−11	0.9515	16	0
RES ENG DES	1.0000	1	15	0.8214	10	6	1.0000	1	15	1.0000	1	0
RES TECHNOL MANAGE	0.3553	25	−4	0.9999	6	15	0.9999	10	11	1.0000	1	9
S AFR J IND ENG	0.0866	40	−2	0.0833	40	−2	0.0866	40	−2	0.1058	40	0
SAFETY SCI	0.6675	16	−2	0.6249	16	−2	0.7478	21	−7	0.7500	21	0
SYSTEMS ENG	0.2091	35	−2	0.1944	34	−1	0.2357	34	−1	0.3334	34	0
TECHNOVATION	1.0000	1	0	1.0000	1	0	1.0000	1	0	1.0000	1	0
TRAV HUMAIN	0.1089	38	3	0.1042	38	3	0.1199	38	3	0.1434	39	−1
# of efficient DMU	5			5			9			10		
% of efficient DMU	11.6%			11.6%			20.9%			23.3%		

Diff IF = ranking in the IF – ranking in each of the BCC models.

half-lives than those of the SCI categories. This implies that social science-related journals have more references per article, but fewer dynamics, than journals related to basic science and engineering. Table 4 lists the 43 journals with their 2011 IF scores and categorical information. The average number of affiliated categories is 2.4, which also demonstrates the high degree of multidisciplinarity of industrial engineering. The median IF of the 43 industrial engineering journals is 0.856. The data for the number of articles and the three output variables were directly collected from JCR 2011, and the values of citation density and citation dynamics were calculated based on Table 3. The data table used for DEA is given in Appendix B.

DEA was run for the four types of BCC models with the 43 industrial engineering journals as DMUs, and the resulting DEA-IF scores for each model are shown in Table 5. Significant differences are found in the ranking of journals between the original IF and DEA-IF. In the BCC1 model, where citation density is added as an input, journals with a low citation density of less than 30, such as *IEEE IND APPL MAG* and *J CONSTR ENG M ASCE*, are more highly ranked. *RES ENG DES*, which ranked 16th in terms of its IF, is ranked at the top in the BCC1 model. On the other hand, a fall in the ranking of journals with high citation density is also observed. For instance, the ranking of *J PROD INNOVAT MANAG* has been changed from third to 17th because it is affiliated with social science fields whose citation densities are very high (above 50). As expected, there is an increase in the ranking of journals with low citation dynamics in the BCC2 model, in which citation dynamics is considered as additional inputs. The journals with a big jump include *ERGONOMICS* (a citation dynamic of 0.8), *J ENG TECHNOL MANAGE* (0.7), and *RES TECHNOL MANAGE* (0.7). In the BCC3 model, the journals that exhibit changes upwards in BCC1 and BCC2

Table 6
DEA-IF in the ARG models.

Journal	ARG1			ARG2			ARG3		
	Score	Rank	Diff BCC4	Score	Rank	Diff BCC4	Score	Rank	Diff BCC4
APPL ERGON	0.6464	20	2	0.6452	20	2	0.6452	18	4
CIRP ANN-MANUF TECHN	0.8627	15	3	0.7356	17	1	0.7347	16	2
COMPUT IND ENG	0.8322	16	3	0.8255	16	3	0.8255	15	4
COMPUT OPER RES	0.9324	14	3	0.9335	13	4	0.9324	11	6
EMJ-ENG MANAG J	0.0760	42	0	0.0763	41	1	0.0760	41	1
ENG ECON	0.9998	12	0	0.9995	12	0	0.9995	10	2
ERGONOMICS	1.0000	1	0	1.0000	1	0	0.9222	12	−11
EUR J IND ENG	0.3631	33	0	0.3631	32	1	0.3631	32	1
HUM FACTORS	0.5606	23	2	0.5692	22	3	0.5606	21	4
IEEE IND APPL MAG	0.4261	29	−15	0.9997	11	3	0.4261	28	−14
IEEE T ENG MANAGE	0.5543	24	2	0.5543	23	3	0.5543	22	4
IEEE T IND INFORM	1.0000	1	0	1.0000	1	0	1.0000	1	0
IIE TRANS	0.4853	25	3	0.4853	25	3	0.4853	24	4
IND ENG	0.0331	43	0	0.0331	43	0	0.0331	43	0
IND MANAGE DATA SYST	0.5734	22	2	0.5055	24	0	0.5024	23	1
IND ROBOT	0.2692	35	0	0.2696	34	1	0.2692	34	1
INT J IND ENG-THEORY	0.0797	41	0	0.0535	42	−1	0.0528	42	−1
INT J IND ERGONOM	0.5893	21	2	0.4572	27	−4	0.4572	26	−3
INT J PROD ECON	1.0000	1	0	0.8537	15	−14	0.8526	14	−13
INT J PROD RES	0.8294	17	3	0.6575	19	1	0.5862	20	0
ISSUES SCI TECHNOL	0.4262	28	3	0.4262	30	1	0.4262	27	4
J CONSTR ENG M ASCE	0.4623	27	−14	0.4455	28	−15	0.3972	30	−17
J ENG TECHNOL MANAGE	1.0000	1	0	1.0000	1	0	1.0000	1	0
J MANAGE ENG	0.4693	26	3	0.4818	26	3	0.4693	25	4
J MANUF SYST	0.6467	19	−4	0.6373	21	−6	0.6373	19	−4
J MATER PROCESS TECH	1.0000	1	0	1.0000	1	0	1.0000	1	0
J PROD INNOVAT MANAG	1.0000	1	0	1.0000	1	0	1.0000	1	0
J QUAL TECHNOL	1.0000	1	0	1.0000	1	0	1.0000	1	0
P I MECH ENG O-J RIS	0.2004	37	0	0.1768	38	−1	0.1768	38	−1
PROBAB ENG INFORM SC	0.4168	30	0	0.4366	29	1	0.4168	29	1
PROD PLAN CONTROL	0.3909	31	1	0.3909	31	1	0.3909	31	1
QUAL ENG	0.9998	11	0	0.9999	10	1	0.9998	9	2
QUAL RELIAB ENG INT	0.3866	32	−5	0.2634	35	−8	0.2526	35	−8
QUAL TECHNOL QUANT M	0.2471	36	0	0.2504	36	0	0.2471	36	0
R&D MAG	0.1780	38	0	0.1780	37	1	0.1780	37	1
RELIAB ENG SYST SAFE	0.9515	13	3	0.9092	14	2	0.9084	13	3
RES ENG DES	1.0000	1	0	1.0000	1	0	1.0000	1	0
RES TECHNOL MANAGE	1.0000	1	0	0.9999	9	−8	0.9999	8	−7
S AFR J IND ENG	0.1058	40	0	0.1058	40	0	0.1058	40	0
SAFETY SCI	0.7500	18	3	0.7171	18	3	0.7171	17	4
SYSTEMS ENG	0.3334	34	0	0.3334	33	1	0.3334	33	1
TECHNOVATION	1.0000	1	0	1.0000	1	0	1.0000	1	0
TRAV HUMAIN	0.1365	39	0	0.1134	39	0	0.1134	39	0
# of efficient DMU	5			5			9		
% of efficient DMU	11.6%			11.6%			20.9%		

Diff BCC4 = ranking in BCC4 – ranking in each of the ARG models.

also enjoy the benefit of field-different citation characteristics. However, when it comes to the BCC4 model, in which total citations are decomposed into external citations and self-citations, little difference is observed from BCC3. This is because journals are allowed to choose much higher weights in an advantageous citation type, thanks to the weight flexibility of DEA, whether they are self-citations or external ones. Yet, it is needless to say that external citations are more valuable than self-citations. This is why we additionally employed the ARG models.

To implement the ARG models, the range of the relative proportions of variables needs to be determined. We imposed restrictions on inputs as well as outputs. The selection of ranges in AR-type models is often based on expert judgment. A series of discussions with experts in bibliometrics and industrial engineering produced the following two restrictions: for inputs, the proportion of the number of articles should be between 30% and 70%; for outputs, the proportion of self-citations should be less than 20%. It should be noted that the two restrictions were made for the purpose of illustration and they are therefore not a rigorous guideline that can be universally applied to different contexts. The rationale for imposing a restriction on inputs is that the number of articles is a more direct input to journals' citation generation processes than are the two field-different characteristics, which should not be ignored in measuring journal performance. The ARG1 and ARG2 models incorporate the first and second restriction, respectively, and the ARG3 model includes both of the restrictions.

Table 6 summarizes the DEA-IF scores in the three ARG models. In the ranking for the ARG1 model, sharp falls are observed for journals that benefited from low citation density in the BCC4 model, such as *IEEE IND APPL MAG* and *J CONSTR ENG M*

Table 7
Weights comparison of *J CONSTR ENG M ASCE*.

Model	DEA-IF		Weights				
	Score	Rank	Articles (I1)	Citation density (I2)	Citation dynamics (I3)	External citations (O2)	Self-citations (O3)
BCC4	0.9997	13	0.0048	0.9206	0.0000	0.0000	0.0127
ARG3	0.3972	30	0.0090	0.1976	0.0000	0.0055	0.0025

ASCE, whose citation densities are the lowest (28.4) and the second lowest (29.2), respectively. This is because many of the weights that were given to citation density in the BCC4 model are allocated to the weights of the number of articles due to the restriction. However, the changes in the rankings of journals with low citation dynamics are not significant (e.g. *J PROD INNOVAT MANAG* and *RES TECHNOL MANAGE*). The reason for this is that enough weights were already attached to the number of journals in the BCC4 model, which do not lead to changes in the DEA-IF. Also, considerable decreases in the rankings of journals with a high rate of self-citations are found in the ARG2 model: *INT J PROD ECON* (34.6%), *J CONSTR ENG M ASCE* (35.1%), and *J MANUF SYST* (39.1%). Their external citation weights in the BCC4 model were all zeros. Restricting the proportion of self-citations led those journals to be ranked much lower. In particular, *INT J PROD ECON*, which was ranked at the top in BCC 4 is now ranked 15th in ARG2. The ARG3 model provides more realistic rankings of industrial journals by incorporating both of the restrictions. It is shown that mirroring the preference in reality through weight restriction results in huge differences in journal rankings. As an example, Table 7 compares the weights of *J CONSTR ENG M ASCE* in BCC4 and ARG3. The journal was evaluated to be almost efficient and ranked in the upper 30% in the BCC4 model because high weights were given to the variables in which it has strengths, citation density and self-citations. No weights were attached to external citations. However, imposing restrictions led the journal to be ranked in the lower 30% because many of the weights were allocated to more important variables. The weight of external citations has now positive values that are larger than those of self-citations, and the weight of the number of articles has been doubled.

It has been shown that there are many differences in the rankings of industrial engineering journals between the original IF scores and the various DEA-IF scores, and also between BCC and ARG. The Wilcoxon signed rank test revealed statistically significant differences in journal rankings between the IF and the BCC4 model ($Z = -.4220$, $p < .0001$), between the IF and the ARG3 model ($Z = -4.975$, $p < .0001$), and between the BCC4 and ARG3 models ($Z = -3.965$, $p < .0001$). Employing DEA to measure the performance of multidisciplinary journals is advantageous because it captures different citation-related characteristics of different fields, which cannot be mirrored in the original IF. However, simply utilizing the BCC model may distort journal rankings due to the weight flexibility of DEA. Taking advantage of the AR model can thus be a good alternative as a reliable measure of journal performance in multidisciplinary fields.

5. Conclusions

This study proposed the DEA-IF as a new measure of journal performance. The DEA-IF models measure journal performance from the perspective of the efficiency of journals' citation generation process. Together with the conventional input and output variables used in calculating the IF, we additionally considered two field-different factors—citation density and citation dynamics—as inputs. We also separately captured the contribution of external citations and self-citations and incorporated their relative importance in measuring journal performance. Our case study on industrial engineering journals demonstrated that there exist significant differences in journal performance rankings between the original IF and the DEA-IF, and that the DEA-IF is a useful measure for the comparison of journal performance in multidisciplinary fields. The DEA-IF is particularly useful for comparing the performance of multidisciplinary journals, but it may also be beneficial when comparing journals from different fields, as long as field-different characteristics are considered. However, we do not insist that the DEA-IF is the most advantageous over the original IF in all respects. Relying on a single measure, the IF, may result in unreliable and unfair outcomes due to its inherent limitations, as pointed out by many researchers. The DEA-IF can be a good supplement to the performance measurement of multidisciplinary journals and the comparison of journals from different fields.

This paper also has some limitations that could serve as fruitful avenues for future research. Firstly, citation density and citation dynamics are not the full set of factors that cause field-to-field variations in the IF. As mentioned earlier, some researchers have insisted that the size of a field is one of the factors that influence the IF. Althouse et al. (2009) found that the fraction of citations of literature indexed in the SCI/SSCI database was the greatest contributor to variation. Incorporating those factors as inputs may produce a more comprehensive indicator of journal performance. Secondly, we took the arithmetic mean for calculating citation density and citation dynamics of an individual journal. However, the degree of relevance of a journal to each field is not exactly the same. It makes more sense to take the weighted average by identifying the contribution rates of related fields in terms of citation frequency. Thirdly, due to the unique characteristics of DEA, DEA-IF does not provide full rankings of journals. Journals with 100% of the DEA-IF scores are considered equally efficient. Over 20% of journals were evaluated to be efficient in the BCC3 and ARG4 models. To address this limitation, some techniques have been developed for the full ranking of DMUs in DEA, such as cross-efficiency (Sexton, Silkman, & Hogan, 1986) and super-efficiency (Andersen & Petersen, 1993). Utilizing these models may enhance the applicability of DEA-IF by improving its discriminant power.

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Appendix A. List of industrial engineering journals

Journal abbreviation	Full title	ISSN
APPL ERGON	Applied Ergonomics	0003-6870
CIRP ANN-MANUF TECHN	CIRP Annals-Manufacturing Technology	0007-8506
COMPUT IND ENG	Computers & Industrial Engineering	0360-8352
COMPUT OPER RES	Computers & Operations Research	0305-0548
EMJ-ENG MANAG J	EMJ-Engineering Management Journal	1042-9247
ENG ECON	Engineering Economist	0013-791X
ERGONOMICS	Ergonomics	0014-0139
EUR J IND ENG	European Journal of Industrial Engineering	1751-5254
HUM FACTORS	Human Factors	0018-7208
IEEE IND APPL MAG	IEEE Industry Applications Magazine	1077-2618
IEEE T ENG MANAGE	IEEE Transactions on Engineering Management	0018-9391
IEEE T IND INFORM	IEEE Transactions on Industrial Informatics	1551-3203
IIE TRANS	IIE Transactions	0740-817X
IND ENG	Industrial Engineer	1542-894X
IND MANAGE DATA SYST	Industrial Management & Data Systems	0263-5577
IND ROBOT	Industrial Robot-An International Journal	0143-991X
INT J IND ENG-THEORY	International Journal of Industrial Engineering-Theory Applications And Practice	1943-670X
INT J IND ERGONOM	International Journal of Industrial Ergonomics	0169-8141
INT J PROD ECON	International Journal of Production Economics	0925-5273
INT J PROD RES	International Journal of Production Research	0020-7543
ISSUES SCI TECHNOL	Issues in Science And Technology	0748-5492
J CONSTR ENG M ASCE	Journal of Construction Engineering and Management-ASCE	0733-9364
J ENG TECHNOL MANAGE	Journal of Engineering and Technology Management	0923-4748
J MANAGE ENG	Journal of Management in Engineering	0742-597X
J MANUF SYST	Journal of Manufacturing Systems	0278-6125
J MATER PROCESS TECH	Journal of Materials Processing Technology	0924-0136
J PROD INNOVAT MANAG	Journal of Product Innovation Management	0737-6782
J QUAL TECHNOL	Journal of Quality Technology	0022-4065
P I MECH ENG O-J RIS	Proceedings of the Institution of Mechanical Engineers Part O-Journal of Risk and Reliability	1748-006X
PROBAB ENG INFORM SC	Probability in the Engineering and Informational Sciences	0269-9648
PROD PLAN CONTROL	Production Planning & Control	0953-7287
QUAL ENG	Quality Engineering	0898-2112
QUAL RELIAB ENG INT	Quality and Reliability Engineering International	0748-8017
QUAL TECHNOL QUANT M	Quality Technology and Quantitative Management	1684-3703
R&D MAG	R&D Magazine	0746-9179
RELIAB ENG SYST SAFE	Reliability Engineering & System Safety	0951-8320
RES ENG DES	Research in Engineering Design	0934-9839
RES TECHNOL MANAGE	Research-Technology Management	0895-6308
S AFR J IND ENG	South African Journal of Industrial Engineering	1012-277X
SAFETY SCI	Safety Science	0925-7535
SYSTEMS ENG	Systems Engineering	1098-1241
TECHNOVATION	Technovation	0166-4972
TRAV HUMAIN	Travail Humain	0041-1868

Appendix B. Data for DEA

Journal	Number of articles (I1)	Citation density (I2)	Citation dynamics (I3)	Total citations (O1)	External citations (O2)	Self-citations (O3)
APPL ERGON	250	34.1	2.2	357	274	83
CIRP ANN-MANUF TECHN	291	31.2	2.7	497	323	174
COMPUT IND ENG	511	33.3	2.7	812	661	151
COMPUT OPER RES	483	32.8	2.2	831	751	80
EMJ-ENG MANAG J	45	34.1	2.2	4	4	0
ENG ECON	34	32.8	1.8	13	6	7
ERGONOMICS	254	46.0	0.8	358	215	143
EUR J IND ENG	46	32.8	1.8	19	17	2

Journal	Number of articles (I1)	Citation density (I2)	Citation dynamics (I3)	Total citations (O1)	External citations (O2)	Self-citations (O3)
HUM FACTORS	107	46.8	1.4	127	107	20
IEEE IND APPL MAG	89	28.4	2.7	57	53	4
IEEE T ENG MANAGE	95	50.0	0.7	91	77	14
IEEE T IND INFORM	102	31.3	2.7	305	200	105
IIE TRANS	153	32.8	1.8	131	121	10
IND ENG	135	34.1	2.2	8	8	0
IND MANAGE DATA SYST	144	33.3	2.7	212	125	87
IND ROBOT	116	32.1	2.7	70	60	10
INT J IND ENG-THEORY	65	31.2	2.7	10	5	5
INT J IND ERGONOM	200	34.1	2.2	252	142	110
INT J PROD ECON	558	31.4	2.3	982	642	340
INT J PROD RES	697	31.4	2.3	777	495	282
ISSUES SCI TECHNOL	69	32.0	1.9	45	45	0
J CONSTR ENG M ASCE	275	29.2	2.9	225	146	79
J ENG TECHNOL MANAGE	31	45.4	0.9	32	22	10
J MANAGE ENG	47	31.2	3.0	37	27	10
J MANUF SYST	36	31.4	2.3	23	14	9
J MATER PROCESS TECH	1035	31.6	3.4	1845	1748	97
J PROD INNOVAT MANAG	110	50.0	0.7	232	183	49
J QUAL TECHNOL	55	30.6	1.2	86	56	30
P I MECH ENG O-J RIS	61	30.7	2.0	24	14	10
PROBAB ENG INFORM SC	67	30.6	1.2	43	31	12
PROD PLAN CONTROL	109	31.4	2.3	79	75	4
QUAL ENG	55	30.2	1.1	41	34	7
QUAL RELIAB ENG INT	140	30.7	2.0	98	49	49
QUAL TECHNOL QUANT M	58	30.6	1.2	16	15	1
R&D MAG	42	34.8	1.7	7	7	0
RELIAB ENG SYST SAFE	339	32.8	1.8	600	441	159
RES ENG DES	37	29.6	2.6	46	29	17
RES TECHNOL MANAGE	61	50.0	0.7	54	39	15
S AFR J IND ENG	65	34.1	2.2	14	11	3
SAFETY SCI	328	32.8	1.8	460	339	121
SYSTEMS ENG	50	32.8	1.8	21	19	2
TECHNOVATION	129	41.3	1.2	424	217	207
TRAV HUMAIN	35	42.0	1.1	5	3	2
Max	1035	50.0	3.4	1845	1748	340
Min	31	28.4	0.7	4	3	0
Average	177	34.7	1.9	241	183	59
Median	102	32.8	2.0	79	56	14

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