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An Input-Output Approach to Analysing the Relative Influence of Journals: The Case of Process Integration Journals

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A journal's influence is commonly measured through well-known metrics such as the h-index, Impact Factor (IF), and Source Normalized Impact per Paper (SNIP); many new metrics have emerged in the recent years to quantify the hierarchy among journals in each discipline. However, a measure including the interdependence among journals through the article reference and citations has not been designed. Interdependence among journals is important to gauge the influence of journals as a source of knowledge or as an avenue for communicating new developments. In this paper, an input-output network model is proposed to quantify the interdependencies that exist in a given cohort of journals. This method yields measures derived from indices used with input-output models in other domains (e.g., economic modelling) that quantifies a journal's influence relative to other journals in the same cohort. This approach is illustrated using publication and citation statistics from four journals that have been regularly associated with PRES. Results show that journals may have high citation ratings but they may not necessarily have a strong influence in driving scientific discussion in other journals.

1. Introduction

Bibliometrics is fast becoming a tool for quantitative evaluation of journal articles, publications and citation data (Thomson Reuters, 2008). The need to effectively compare the performance of scientific output in gauging where one will submit a manuscript and the relevance of the publication within a discipline has brought about developments in the field of bibliometrics. Numerous measures have already been developed to assess the importance of journals. The most popular ones are the Impact Factor (IF) for journals indexed by Thomson Reuters, Source Normalized Impact per Paper (SNIP) for journals indexed by Scopus and h-index. While IF and SNIP are solely used for journals, h-index is more flexible such that it can be used to compare the relevance of the cumulative work of individuals, journals and even countries as developed by Hirsch (2005). The h-index has been extended to account for self-citations (Schreiber, 2007), time (Egghe, 2007) and multiple coauthorship (Hirsch, 2010). Hodge and Lacasse (2010) argue that the h-index is a better measure for evaluating journal quality compared to IF. Each database prescribes a metric for estimating the scientific impact of journals. Bakkalbasi et al. (2006) recommends the use of a specific metric between Google Scholar, Scopus and Web of Science, depending on the number of publications in the specified field.
The decision for allocating government funds to support university research activities is based on several criteria, a large part of which is also publications, but concerns on measuring the quality of the publications is also a concern for such agencies (Butler, 2002). More specifically, governments tend to review the scientific impact of their research spending (King, 2002). These measures account for the citations for the journals and articles published in it, however, a measure for considering the interaction between journals or journal articles has yet to be developed. This paper introduces a method for measuring a journal's influence through input-output analysis and decision making trial and evaluation laboratory.

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2. Input-output analysis

Input-output (I-O) analysis is a methodology that illustrates the interactions between various sectors of the economy within a system of linear equations (Leontief, 1936). The I-O model can be specified as: .

$$\mathbf{Ax+y=x} \tag{1}$$

where **A** is an *n x n* matrix of technical coefficients with elements a_{ij} that denotes the input requirement of sector *j* from sector *i* normalized with respect to the total input requirement of sector *j*, **x** is the total output vector, and **y** is the final demand vector. It can be noted that the **Ax** in Eq(1) represents the intermediate demand, which is used for further processing, while the final demand vector responds directly to the requirements of end-users.
By considering the interdependent relationships that exist within sectors, such that an economic may need inputs from itself and other sectors to produce its output, a sector's influence may not only be due to its sector size but also due to the dependence of other sectors to its output as an input for their production.
Impact assessment using I-O analysis can be done using multiplier analysis and measuring backward and forward linkages (Miller and Blair, 2009). Eq(1) can be rewritten as:

$$\mathbf{(I–A)^{-1}y=x} \tag{2}$$

where the column sum of $\mathbf{(I–A)^{-1}}$ yields the output multiplier attributable to an increase in the final demand. Backward linkage measures an economic sector's dependence on other sector's inputs for its production. It is specified as:

$$\overline{BL_j} = \frac{\sum_{i=1}^{n} a_{ij}}{(\frac{1}{n})\sum_{i=1}^{n} a_{ij} \sum_{j=1}^{n} a_{ij}} \tag{3}$$

where $\overline{BL_j}$ is the backward linkage of sector *j* and a_{ij} is the ij^{th} element of the technical coefficients matrix. Note that it is normalized over the average of the backward linkages of all sectors such that a value greater than one denotes above average backward linkage to other sectors. The backward linkage focuses on the influence of the sector as a consumer of other sector's input while not addressing other sector's demand for its output for further production. Thus, the development of net backward linkage (Dietzenbacher, 2005):

$$NBL_j = \frac{j^{th}\ column\ sum\ of\ (\mathbf{I}-\mathbf{A})^{-1}\hat{\mathbf{y}}}{j^{th}\ row\ sum\ of\ (\mathbf{I}-\mathbf{A})^{-1}\hat{\mathbf{y}}} \tag{4}$$

Using this measure, it can be determined whether a sector is more important as a contributor for other sectors' production or as a consumer of another sectors output.
In addition to linkages, distance between economic sectors, measured through the average steps required to affect the value of production in another sector due to an exogenous change to a sector, can also serve as a measure of influence within sectors. The average propagation length (APL) developed in Dietzenbacher et al. (2005) can be measured as:

$$v_{ij} = \begin{cases} \frac{h_{ij}}{(l_{ij}-\delta_{ij})} & if \quad l_{ij}-\delta_{ij} > 0 \\ 0 & if \quad l_{ij}-\delta_{ij} = 0 \end{cases} \tag{5}$$

where h_{ij} is the ij^{th} element of **H**=**L**(**L-I**), **L**=(**I-A**)$^{-1}$, and δ_{ij} is the Kronecker delta which has a value of 1 if *i=j* and 0 otherwise. Given that this will yield a matrix, a composite measure can be derived through Eq(6)

$$Composite\ APL_i = \sum_{i=1}^{n} APL_{ij} + \sum_{j=1}^{n} APL_{ij} - 2APL_{ii} \tag{6}$$

which is adapted from the diversity of reach component of the vulnerability index by Yu et al. (2014).

3. Decision making trial and evaluation laboratory

The Decision Making Trial and Evaluation Laboratory (DEMATEL) is a modelling technique that shows the influence of one factor to another through a diagram (Lin, 2013). It can be used to show the interrelationships between factors considered in the decision making process. The procedure of implementing DEMATEL requires the construction of an initial direct relation matrix with *n* rows and columns, $\mathbf{A_d}$ which shows the pairwise degree of influence to which factor *i* affects factor *j* for all *n* factors. This is then normalized through dividing each element of the initial direct relation matrix by the maximum row sum such that the overall direct relation matrix, **B**, is specified as:

$$\mathbf{B} = [\mathrm{b_{ij}}]_{\mathrm{nxn}} = \frac{\mathbf{A_d}}{\max\limits_{1\le i\le n} \sum_{j=1}^{n} a_{ijd}} \tag{7}$$

The total relation matrix, **C**, is derived from the overall direct relation matrix, **B**, such that

$$\mathbf{C} = \left[c_{ij}\right]_{nxn} = \mathbf{B}(\mathbf{I} - \mathbf{B})^{-1} \quad (8)$$

where **I** is the identity matrix. The elements of the total relation matrix will then be used to compute for the prominence and net cause-effect values for each factor.

$$\mathbf{D} = \left[d_{ij}\right]_{nx1} = \left[\sum_{j=1}^{n} c_{ij}\right]_{nx1} \quad (9)$$

$$\mathbf{E} = \left[e_{ij}\right]_{1xn} = \left[\sum_{i=1}^{n} c_{ij}\right]_{1xn} \quad (10)$$

where **D+E** measures the prominence and **D-E** measures the net cause-effect values for each factor, which will be plotted on to a digraph.

4. Input-output and DEMATEL approach for measuring journal influence

During the early stages of developing citation indices, Leontief (1996) proposed the use of the structure of the I-O table to model the flow of scientific knowledge, however, no specific direction was developed to evaluate such flows. Several studies have developed I-O tables that address innovation flows through accounting for research and development spending. Frenken (2002) implemented an I-O approach to illustrate collaborative culture in an integrated region. Tabatabaei and Beheshti (2008) explored the use of I-O tables for measuring the flow of ideas between scientific disciplines. This idea was further built upon into gauging the influence of a subfield of scientific disciplines and their influence among each other (Shen et al., 2010). However, to date, the influence of journals among each other have not been measured. Furthermore, this study uses the DEMATEL to measure the prominence of a journal as a source of ideas or as an innovator from ideas. Initially developed by Battelle Memorial Institute to visualize causal relationships in complex societies (Gabus and Fontela, 1972, Wu and Lee, 2007), DEMATEL has been used to evaluate risk factors in supply chain management (Song et al., 2017), performance evaluation of transportation zones (Ranjan, 2016) and identifying barriers to implementing industrial symbiosis networks (Bacudio et al., 2016). It has also been applied to analysing the effectiveness of investing in research and development through technology spillovers (Park et al., 2017) and resource allocation in a university setting (Rahimnia and Kargozar, 2016).

5. Case study

To illustrate the proposed measure, this paper considers the case of process integration journals that have been regularly associated with the Process Integration, Modelling and Optimisation for Energy Saving and Pollution Reduction (PRES) Conference. These journals are Clean Technologies and Environmental Policy (CTEP), Journal of Cleaner Production (JCLP), ENERGY, and Applied Thermal Engineering (ATE).
Table 1 presents the number of citations from articles published in CTEP, JCLP, ENERGY and ATE in 2015 by articles published in the said journals and other journals in 2015. This data was updated as of February 15, 2017 and was taken from Scopus (n.d.). For example, the first row shows that articles published in CTEP last 2015 were cited by 11 articles published in 2015 in CTEP, 8 articles published in 2015 in JCLP, 35 articles published in 2015 in other journals, summing up to 54 citations. In an I-O framework, the four journals represent the economic sectors, “others” represents final demand vector and the “total citations” represent the output vector. In this context, the four journals are inter-related since they cover similar disciplines, and they each serve as a potential source of citations. All other journals are classified as an external part of the system. Total citations from the four journals and all other journals are collectively treated as total yield.

Table 1: Number of citations from source journal for the year 2015 by articles published in 2015 as of 15.2.2017

	Journals with citations from the Source Journal					
Source Journal	CTEP	JCLP	ENERGY	ATE	Others	Total Citations
CTEP	11	8	0	0	35	54
JCLP	3	179	11	4	760	957
ENERGY	2	2	242	16	477	739
ATE	2	8	49	158	429	646

Based on Table 1, the technical coefficients matrix, **A**, is derived in Table 2. Each element, a_{ij}, represents the percentage of citations in journal j attributable to the source journals i.

Table 2: Technical coefficients matrix

Source Journal	Journals with citations from the Source Journal CTEP	JCLP	ENERGY	ATE
CTEP	0.2037	0.0084	0.0000	0.0000
JCLP	0.0556	0.1870	0.0149	0.0062
ENERGY	0.0370	0.0021	0.3275	0.0248
ATE	0.0370	0.0084	0.0663	0.2446

Table 3 presents the APL for the four journals. The APL matrix shows the distance of journals in the j^{th} column to the source journals in the i^{th} row. It can be noted that as values increase, the source journal's influence is reduced as it takes more steps to reach journal on the column.

Table 3: Average Propagation Length

Source Journal	Journals with citations from the Source Journal CTEP	JCLP	ENERGY	ATE
CTEP	1.2612	1.4881	3.0308	2.9420
JCLP	1.5198	1.2374	1.7750	1.6862
ENERGY	1.8016	2.0480	1.5053	1.8214
ATE	1.7409	1.6653	1.8234	1.3483

Table 4 summarizes the metrics derived using the I-O approach which include the multiplier, backward linkage, net backward linkage, and the composite APL for each journal. In addition, the h-index (ScimagoLab, 2017) and SNIP (Scopus, 2017) are provided in the Table 4. Based on the rankings of each metric, it is clear that each metric shows a different perspective of a journal's influence. For the multiplier, it can be observed that ENERGY ranks the highest such that an additional citation by another journal will yield the greatest return in terms of total citations to all four journals, followed by CTEP, ATE and JCLP. In terms of journal dependence towards the other three PRES affiliated journals, ENERGY has the highest linkage, followed by CTEP, ATE and JCLP. In terms of net backward linkages, ENERGY still yields the highest metric with value greater than 1 which implies that it yields higher citations for the four journals considered relative to the citations that the other journals yield for ENERGY. It is interesting to find that JCLP has a relatively close value to ENERGY in this metric. In terms of Composite APL, it is better to have a lower value which translates to higher influence if the distance between the journals are shorter. It is also noticeable that ENERGY, which used to dominate the other metrics is seen only as third in this aspect. Referring to the data in Table 1, it can be seen that ENERGY has a high incidence of self-citation, and its influence towards other journals is not that high compared to JCLP and ATE.

Table 4: Journal Influence Metrics

Journal	Multiplier	Rank	Backward Linkage	Rank	Net Backward Linkage	Rank	Composite APL	Rank	h-index	Rank	SNIP	Rank
CTEP	1.4853	2	0.2725	2	0.9628	3	12.5232	4	27	4	1.180	4
JCLP	1.2639	4	0.1683	4	1.0037	2	10.1824	1	96	2	2.272	1
ENERGY	1.6518	1	0.3340	1	1.0661	1	12.3002	3	111	1	1.898	2
ATE	1.3883	3	0.2252	3	0.9219	4	11.6790	2	94	3	1.773	3

Comparing the total number of citations and the citations within the four journals considered in this article, JCLP has the highest number of citations, however, it can be inferred that JCLP has a lower score since it covers a broader scope of scientific disciplines and might not be number of articles related to those published in the other three journals might not be as many. The linkages measure the interactions, or the influence of the journal within the specific subdiscipline.
Through DEMATEL, the influence of the journals can be illustrated through a digraph with values derived from the total relation matrix provided in Table 5.

Table 5: Total Relation Matrix

Source Journal	Journals with citations from the Source Journal			
	CTEP	JCLP	ENERGY	ATE
CTEP	0.0117	0.0104	0.0002	0.0000
JCLP	0.0040	0.2302	0.0194	0.0065
ENERGY	0.0029	0.0038	0.3404	0.0269
ATE	0.0028	0.0126	0.0824	0.1995

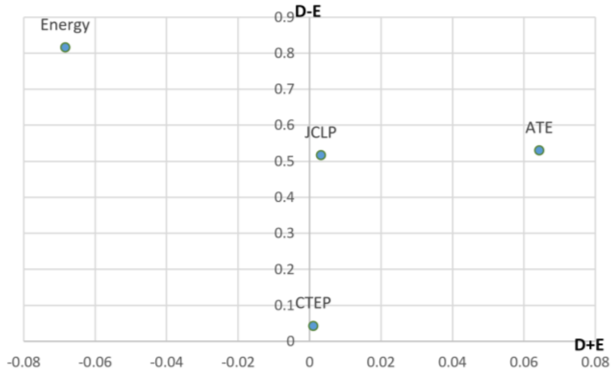

Figure 1: Causal-effect diagram

Figure 1 illustrates the cause-effect relationship of each journal relative to the others. Based on the diagram, it can be inferred that JCLP and ATE are the journals that are prominent in spur conversations and ideas in the scientific community through citations. It can also be noted that these citations are not confined within the four journals considered in this study. CTEP, though more prominent than ENERGY, does not have a high influence through citations. It is more dependent on other journals. ENERGY, on the other hand, is not too prominent in terms of influencing other journals and has a high tendency of stimulating scientific discussions within itself.

6. Conclusions

Existing measures of journal influence have been compared with the I-O based metrics. While the h-index and SNIP have relatively similar ranks, the I-O metrics for journal influence vary broadly even within the same framework. Depending on the goals and how one defines a journal's influence, the various I-O based metrics may be converted into a single metric through assigning weights for each component. The current work looks into the relative influence of journals, it can be extended to account for the relative influence of an article compared to another article. This is particularly useful in measuring the spillover effects and the knowledge further generated resulting from scientific work. This work can be further extended to account for multiple time periods.

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