Making scientometric sense out of NIRF scores

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The National Institutional Ranking Framework (NIRF) 2016 rankings have released a wealth of bibliometric data that is otherwise difficult to collect. We have closely examined the top 20 engineering institutions in engineering from the NIRF list from the point of view of research excellence alone, as is done in most international university ranking exercises. Unlike the NIRF score, which is one single number, we now decompose performance into a size-dependent exergy term and a size-independent productivity term. The IITs at Bombay and Kharagpur stand out in terms of research excellence. Another insight is the excellent promise shown by the new IITs at Ropar–Rupnagar and Indore.

Keywords: Bibliometrics, National Institutional Ranking Framework, research evaluation, size-dependence, size-independence.

THE National Institutional Ranking Framework (NIRF) has just released its maiden rankings of higher educational institutions across the country. Unlike other international university ranking schemes which are based on educational and research excellence[1–4], here very broad but often fuzzy parameters are used which cover aspects classified broadly under the heads ‘Teaching, Learning and Resources’, ‘Research and Professional Practices’, ‘Graduation Outcomes’, ‘Outreach and Inclusivity’, and ‘Perception’. These five broad heads are then elaborated through further sub-heads, with weights assigned to each broad head, and more weights assigned to the sub-heads within each head. Such complex marking and weighting schemes further contribute to the fuzziness. For each sub-head, a score is generated using suitably proposed metrics, and the sub-head scores are then added to obtain scores for each individual head. The overall score is computed based on the weights allotted to each head. The overall score can take a maximum value of 100. The institutions are finally rank-ordered based on their scores. Size-dependent and size-independent parameters[5] are combined, mixed, added and multiplied without any guiding logic like consistency of units or random additivity or random multiplicativity. With such an intricate scheme, it is impossible to judge if the final NIRF score is size-dependent or size-independent or a composite of these parameters.

In this paper, we confine attention only to the aspect of research excellence as measured by publications, citations and impact from three different bibliometric databases for the top 20 engineering institutions ranked in 2016.

Table 1 shows how the scientometric or bibliometric assessment is done for the top institution in the engineering category according to NIRF 2016, namely the Indian Institute of Technology (IIT) at Madras. We start with one primary size-dependent input parameter: the number of regular faculty, F. We have bibliometric data from three databases, the Indian Citation Index, Scopus and Web of Science. The total number of publications reported P, and the total number of citations reported for the three-year window 2012–2014 are the basic bibliometic data. From this, we can compute from each database, the impact $i = C/P$, which is an accepted proxy for the quality of the work reported in that database by the institution. Note that P is size-dependent proxy of quantity of research output, i is a size-independent proxy of quality of research output and C is a composite size-dependent indicator which combines quality and quantity.

The Indian Citation Index confines attention to papers published in and citations within a core set of Indian journals. Scopus and Web of Science are international databases of leading journals with a considerable overlap, and which also include a very select set of Indian journals. A single-valued composite outcome indicator for the research performance of each institution from each database can be computed as the second-order indicator[6] called the exergy term from the quantity (size) and quality (excellence) indicators, $x = i^2P = iC$. As this returns a scalar value for each database, we compute $X = \sum x$ as a proxy for the total research output of the institution. This will mean multiple counting in a few cases but as the exact degree of overlap of the journals in the databases is not known, this is the best that can be done. We see that

Table 1. Bibliometric assessment for the top institution in the Engineering category according to NIRF 2016, namely the Indian Institute of Technology at Madras

Institute name		Indian Institute of Technology, Madras
No. of regular faculty	F	540
Publication details		
Indian citation index 2012–14	Papers P	204
	Citations C	28
	impact i = C/P	0.14
Scopus 2012–14	Papers P	4302
	Citations C	16,622
	Impact $i = C/P$	3.86
Web of Science 2012–14	Papers P	2920
	Citations C	14,477
	Impact $i = C/P$	4.96
Total eXergy	$X = \sum iC$	136,002.85
Per capita eXergy	X/F	251.86
NIRF score		89.41

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Table 2. Summary of bibliometric indicators for the top twenty institutions in the Engineering category according to NIRF 2016

NIRF rank		F	X	X/F	NIRF score
1	Indian Institute of Technology, Madras	540	136,002.85	251.86	89.41
2	Indian Institute of Technology, Bombay	565	213,436.11	377.76	87.66
3	Indian Institute of Technology, Kharagpur	686	198,783.18	289.77	83.91
4	Indian Institute of Technology, Delhi	497	140,364.89	282.42	82.02
5	Indian Institute of Technology, Kanpur	389	140,896.83	362.20	81.07
6	Indian Institute of Technology, Roorkee	416	138,282.81	332.41	78.68
7	Indian Institute of Technology, Hyderabad	139	22,154.29	159.38	77.22
8	Indian Institute of Technology, Gandhinagar	81	5,884.90	72.65	75.20
9	Indian Institute of Technology, Ropar-Rupnagar	63	36,847.40	584.88	74.88
10	Indian Institute of Technology, Patna	74	10,289.63	139.05	74.68
11	Indian Institute of Technology, North Guwahati	361	121,724.58	337.19	74.62
12	National Institute of Technology, Tiruchirappalli	220	49,590.60	225.41	74.45
13	Vellore Institute of Technology	1293	42,298.64	32.71	74.40
14	Indian Institute of Technology (Banaras Hindu University), Varanasi	228	23,491.93	103.03	74.39
15	Sardar Vallabhbhai National Institute of Technology	187	28,560.64	152.73	73.13
16	Indian Institute of Technology, Indore	77	69,539.21	903.11	72.00
17	Birla Institute of Technology	216	18,060.41	83.61	71.80
18	Visvesvaraya National Institute of Technology, Nagpur (Deemed University)-Nagpur	181	6,778.33	37.45	71.29
19	National Institute of Technology, Rourkela-Rourkela	279	43,048.93	154.30	70.80
20	Indian Institute of Technology, Mandi	62	8,213.95	132.48	70.32
	Pearson's correlation		X	X/F	NIRF score
	X		1.00	0.39	0.83
	X/F		0.39	1.00	0.17
	NIRF score		0.83	0.17	1.00

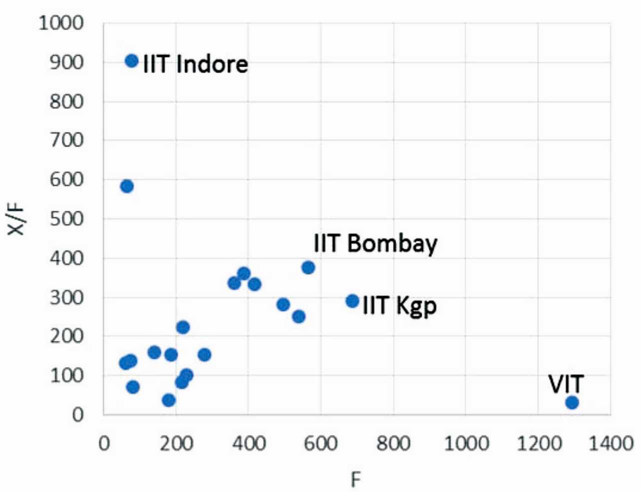

Figure 1. Scatter plot of exergy per faculty (X/F) versus faculty strength (F).

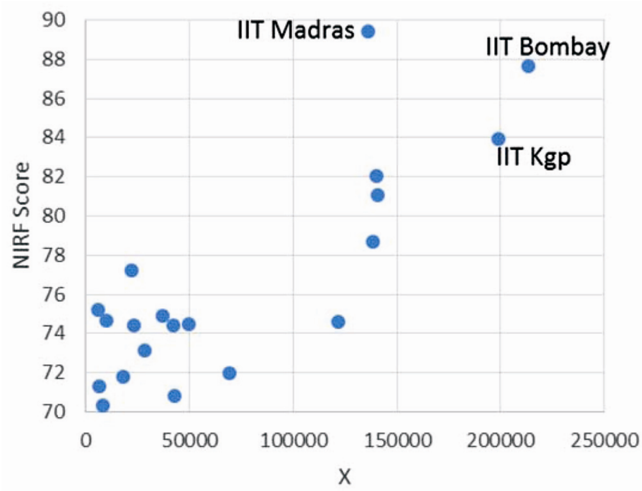

Figure 2. Scatter plot of NIRF score versus exergy.

X is a scalar measure of total research output, and therefore X/F is a size-independent measure of productivity of the institution.

This exercise is repeated for the top 20 institutions in the NIRF 2016 rankings for engineering.

Table 2 is a summary of bibliometric indicators of the top 20 institutions in the Engineering category according to NIRF 2016. Within these there is a huge range in size, from IIT, Mandi with 62 faculty members to Vellore Institute of Technology (VIT) with 1293 regular faculty, which is more than twenty times as big. IIT, Gandhinagar has the lowest output as measured in exergy terms (5884.90) and IIT, Bombay with the highest (213436.11), is thirty-six times bigger. In terms of per capita output, we find VIT to be the lowest performer and IIT, Indore to be the best performer, by a factor of 27.61. This range is not seen in the NIRF scores, where the academic aspect which accounts for only a small fraction of the total score along with scores from all the other heads and sub-heads have been telescoped into a narrow band (IIT, Mandi at 70.32 and IIT, Madras at 89.41). This suggests that NIRF is unable to capture the various random multiplicative processes involved in finding a performance score.

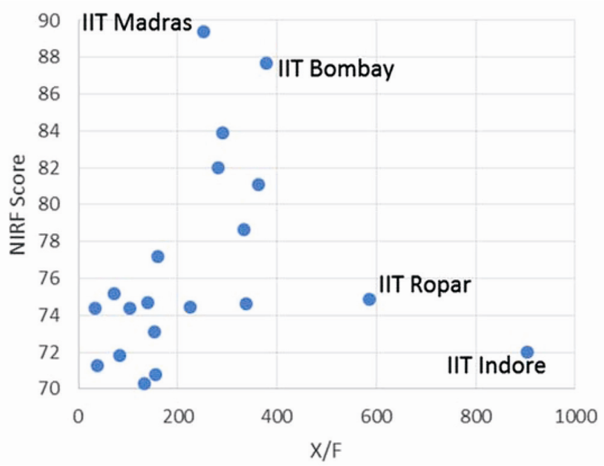

Figure 3. Scatter plot of NIRF score versus exergy per faculty (*X*/*F*).

The Pearson's correlations are also shown in Table 2 and Figures 1–3 show the key relationships between *X*/*F*, *X* and NIRF score as scatter plots. We see that the IITs at Bombay and Kharagpur stand out in terms of research excellence. Another insight is the excellent promise shown by the new IITs at Ropar-Rupnagar and Indore.

We use the bibliometric data that has been released through the NIRF 2016 rankings to see how the top twenty engineering institutions fare if only research excellence is considered as is done in major ranking exercises[1–4]. Unlike the NIRF score, which is one single number, we now decompose performance into a size-dependent exergy term and a size-independent productivity term. We see that the IITs at Bombay and Kharagpur stand out in terms of research excellence. Another insight is the excellent promise shown by the new IITs at Ropar-Rupnagar and Indore.

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Hierarchy of parameters influencing cutting performance of surface miner through artificial intelligence and statistical methods

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Applicability of a surface miner (SM) must be based on a careful assessment of intact rock and rock mass properties. A detailed literature review was made to identify different parameters influencing the performance of various types of cutting machines deployed in different parts of the world. The critical parameters influencing the production, diesel consumption and pick consumption of SM in Indian coal and limestone mines, were identified through artificial neural network (ANN) technique and screened by correlation coefficient analysis. Parameters that were common in both ANN and correlation analysis were grouped under critical category and others in semi-critical category.

Keywords: Artificial neural network, intact rock, rock mass, surface miner.

INTACT rock, rock mass and machine parameters are broad key parameters that play a key role in cutting performance. Cutting performance is generally evaluated by various parameters such as, production, specific energy, chip size of cut material, cutting force, pick wear, pick consumption, etc. The present study describes an approach to identify critical parameters that affect the performance of surface miner (SM) based on field data collection from various project areas in India. The purpose of identification of the influencing parameters is to understand their relevant importance in the performance of SM and subsequently use them for predicting its performance. Field investigations were conducted in six mines (three each in coal and limestone mines), spread across India representing varied rock mass parameters. The present study conducted under varied rock mass conditions was confined to SM application only. Artificial neural network (ANN) and correlation tools were used to arrive at critical parameters influencing performance of SM in Indian geo-mining conditions with respect to production, diesel consumption and pick consumption.

The following are the intact rock parameters: Rock density: Dry density is a key property that affects specific energy (SE) while cutting[1]. A rock with higher specific gravity or density will need higher SE in cutting. Kahraman

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