Chapter 10
Scientific Impact Vitality: The Citation Currency Ratio and Citation Currency Exergy Indicators

Gangan Prathap and Dimitrios Katsaros and Yannis Manolopoulos

Abstract Publication and impact measures for individual scientists are used worldwide for various purposes such as funding, promotion, and consequently, the development of such indicators comprises a fertile research area. In this article, we propose two simple citation-based indicators, a dimensionless *citation currency ratio* (CCR) and a size-dependent *citation currency exergy* (CCX) which are noncumulative indicators measuring current citation performance. These help to identify scientists who are at different stages of their career, with rising, steady, or fading visibility. Using a small-scale coherent sample of scientists from DLPB, Google Scholar and the recently published so-called Stanford[1] list [8], we demonstrate the applicability of these ideas and show that our methods provide substantial promise for future use.

10.1 Introduction

Like old soldiers, old scientists never die; their works' impact just fades away.
The quest for scientometric indicators which capture significant aspects of individual scientists performance keeps consistently growing the last fifteen years because of

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[1] It is for ease of reference only that this dataset is called "Stanford"; It is clear that it has not been endorsed by any means from Stanford authorities.

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the availability of big scholarly data by bibliographic databases, and also because of their use in bureaucratic decision-making, despite criticism against such practises. Several hundreds of indicators for quantifying an individual scientist's performance have been proposed the last decade which use more and more detailed information concerning publication number, citation number citation networks, paper age, citation age, co-authorship networks, centrality measures, and so on. The great majority of these indicators are cumulative, i.e., they never decline; thus they favor those scientists of greater "scientific age", and/or they can not distinguish the scientists whose performance in terms of citation-based impact is getting significant in the present, and/or are rising stars.

Here, we seek to develop indicators that will capture the performance of a scientist whose citation-based impact per year is getting (gradually) bigger; to describe it in different words, we aim at developing indicators which can detect that the scientist's impact on an annual basis is not *fading away*. We term this characteristic of a scientist's impact evolution as the *vitality* of his/her research. This notion is different that the concept of rising star [4] or trendsetter [22]. Therefore, our goal is to develop scientometric indicators to capture the vitality of scientific impact, and in particular we are interested in developing indicators which will (practically) be noncumulative, and also they will be easy to calculate.

In this context, we propose two simple to calculate indicators, namely a dimensionless *citation currency ratio* (CCR), and a size-dependent *citation currency exergy* (CCX) to capture these trends quantitatively. We study a coherent cohort of scientists to see how this happens across the board. We use data from DPLB and Google Scholar as well as the recently published Stanford list [8], to demonstrate the applicability of these ideas. The obtained results are encouraging showing promise that these indicators can be used in the future to capture the aforementioned aspect of citation-based performance of a scientist.

The rest of this article is organized as follows: Sect. 10.2 surveys the related work. Sect. 10.3 reviews some basic definitions from past literature and develops the new scientometric indicators. Sect. 10.4 presents two case-studies to assert the usefulness of the new indicators, and finally Sect. 10.5 concludes the article.

10.2 Related Work

During the last fifteen years the research efforts pertaining to scientometric indicators have been growing steadily, especially after the development of large bibliographic databases, such as Google Scholar, Microsoft Academic, Elsevier Scopus, etc. At that time, the introduction of the Hirsch *h*-index [7] was a path-breaking idea that among other scientific consequences, it popularized the concept of scientometric indicators. The work in [13] offers solid proof that the research pertaining to the *h*-index has been growing after 2005 (besides some small slowing down in 2014 and in 2017), and this is the general trend with other indicators as well. Surveys of such indicators can be found in [24, 25]. Since the focus of the present article is about the indicators capturing the aggregated citations' dynamics (i.e., *evolution in time*) of scientists, in the rest of this section, we will survey only such indicators.

The goal of identifying young (in terms of career) scientists who currently have relatively low profiles, but may eventually emerge as prominent scientists – the so-called *rising star scientists* – is a recent, challenging, hot topic, and it is extended to other social media, e.g., in geo-social networks [14]. *ScholarRank* was proposed in [27] which considers the citation counts of authors, the mutual influence among coauthors and the mutual reinforce process among different entities in academic networks to infer who are expected to increase their performance dramatically. In [16] several performance indicators are compiled for each scholar and monitored over time; then these indicators are used in a clustering framework which groups the scholars into categories. *StarRank* was proposed in [15] which is an improved *PageRank* [12] method to calculate the initial "promise" of rising stars, and then this "promise" is diffused in an artificial social network constructed via explicit and implicit links, and finally a prediction of a scholars' ranking in the future is conducted. Departing from existing methods for rising star detection, which explore the co-author networks or citation networks, the work reported in [3] uses an article's textual content, and [6] uses a form of similarity clustering of scholars. Finally, [4] presents a survey on rising star identification by classifying existing methods into ranking-, prediction-, clustering-, and analysis-based methods, and also discusses the pros and cons of these methods.

Another group of indicators that is related to the present work includes those indicators which apply an aging mechanism to citations and articles to identify the scientists whose performance degrades in time. Two popular indices of this group are the *trend h-index* and *contemporary h-index* [10, 22] which however have been described in the context of the *h*-index mechanism, capturing both productivity and impact. Nevertheless, the trend/contemporary *h*-index's idea of citation/paper aging can be applied in isolation to a scientist's citation set. Along, the same line but slightly different are the *Optimum-time* and *Speed of withdrawal* [2]. Finally, the idea of measuring by approximation the citation acceleration [26] considers also temporal aspects, and thus it is partially relevant to the present work.

Moreover, our work is only remotely related to identification of sleeping beauties in science [11] and the subsequent work on the topic concerning the rediscovering paper of a sleeping beauty [23], how sleeping beauties get cited in patents [21], the derivative analysis of sleeping beauties' citation curves [5], and case studies [1] because those works deal with individual article's temporal citation performance.

Almost all aforementioned works are based on extensive citation network analysis, and/or exploitation of the timestamp of each citation. Our present work departs from these practices, and it is based only on citation information received at a specific year and on total citations received up to this year, thus making the calculation of the proposed indicators far more less computationally expensive.

10.3 The New Scientometric Indicators

We will start by presenting some scientometric indicators from earlier works which are necessary for defining the new ones. So firstly, we will provide the definitions of energy and exergy, and in the next subsection, we will introduce the *citation currency ratio* and *citation currency exergy*. To facilitate our presentation, we will make use of the symbols reported in Table 10.1.

In search of a single number indicator able to adequately describe the whole performance of a scientist, the concepts of energy, exergy and entropy were introduced in [19] borrowing those terms from thermodynamics. When fractional citation counting [9] is necessary, these concepts can be extended appropriately [17]. So, the energy of a single paper which has received c_i citations is equal – by definition – to c_i^2. We recall the following definitions:

Definition 1 (from [19]) The Energy of a set of publications $P = \{p_1, p_2, \ldots, p_n\}$ (i.e., $||P|| = n$), where the article p_i has received c_i citations is defined as follows:

$$E \equiv \sum_{i=1}^{||P||} c_i^2. \tag{10.1}$$

Definition 2 (from [19]) The Exergy of a set of publications $P = \{p_1, p_2, \ldots, p_n\}$ (i.e., $||P|| = n$), where the article p_i has received c_i citations is defined as follows:

$$X = \frac{1}{||P||}\left(\sum_{i=1}^{||P||} c_i\right)^2 = \frac{C^2}{||P||}. \tag{10.2}$$

Table 10.1 The set of symbols used throughout the article. The above quantities are assumed to have been measured during a specific time window, e.g., from 1996 to 2019

Definition	Symbol
Set of articles published by a scientist	P
Cardinality of the set of articles published by a scientist	$\|\|P\|\|$
Citations received by the i-th article	c_i
Total number of citations received by all P articles	C
Citations received only during year yr (by articles published until year yr)	${}^{yr}c$ e.g., ${}^{2015}c$
Total (cumulative) citations received up until year yr (by articles published until year yr)	${}^{yr}C$ e.g., ${}^{2019}C$
Energy of a set of publications (e.g., of P)	E
Exergy of a set of publications (e.g., of P)	X
Entropy of a set of publications (e.g., of P)	S

Apparently, it holds that $E > X$. The difference is called *entropy (S)* in [19], i.e., $S = E - X$.

The exergy X is an excellent single, scalar measure of a scientist's performance, especially when only aggregate information, i.e., C and $||P||$ is available. The entropy on the other hand measures how much "uneven" (unordered) is the scientist's publication portfolio; it measures whether the published articles of a scientist continue to attract citations in the course of time or if his/her impact is "fading away".

10.3.1 The Citation Currency Ratio and Citation Currency Exergy Indicators

The astute reader will have realized by now that in our scientometric world, exergy corresponds to the portion of "impact flow", and thus it is a measure of how the impact of a scientist degrades (decays) over the years. However, exergy is defined using cumulative citation performance, and just like the raw measures ${}^{yr}c$ and ${}^{yr}C$ tends to be a proxy for cumulative impact. Both ${}^{yr}c$ and ${}^{yr}C$ vary by orders of magnitude depending on the citation intensity of the field or subfield, and on the size of collaboration. Over a lifetime, there are scientists who have collaborated with large numbers of co-workers, whereas others have worked in much smaller teams.

To deal with these issues and introduce some notion of fairness, we introduce the *Citation Currency Ratio* defined as follows:

Definition 3 The *Citation Currency Ratio (CCR)* of a scientist in a specific year *yr* is the ratio of the citations ${}^{yr}c$ received during that year to the cumulative number ${}^{yr}C$ of citations until that year, i.e.,:

$$ {}^{yr}CCR = \frac{{}^{yr}c}{{}^{yr}C}, \tag{10.3} $$

or dropping year information when it is clear at which year it is being calculated:

$$ CCR = \frac{c}{C}. \tag{10.4} $$

CCR is a dimensionless parameter; it starts from a value of 1 and never exceeds this number, diminishing to zero as the portfolio fades away. This is a welcome feature in that at the very beginning of a scientific career one would start with a CCR value of 1, whereas at the very end, when the portfolio of work ceases to gather citations, it becomes zero. Note that at each stage, CCR is like a size-independent quality term; using the quality-quasity-quantity terminology from [18], c is a quasity term, and C is a quantity term.

Starting from this new indicator, we propose a second-order composite exergy term [20] defined as follows:

Definition 4 The *Citation Currency Exergy (CCX)* of a scientist in a specific year *yr* is the product of the CCR times the number of citations ${}^{yr}c$ received during that year, i.e.,:

$$^{yr}CCX = {}^{yr}CCR \times {}^{yr}c \implies {}^{yr}CCX = \frac{^{yr}c^2}{^{yr}C}, \tag{10.5}$$

or dropping year information when it is clear at which year it is being calculated:

$$CCX = CCR \times c \implies CCX = \frac{c^2}{C}. \tag{10.6}$$

This is a size-dependent term and gives a relative measure of current activity in comparison with cumulative activity.

Along the same lines of methodology as previously, we can also compute currency indicators for the h-index and for $i10$. We use the 5-year values of these as the "recent" metrics. In each case we get the ratios, hCR and $i10R$, and the respective exergies hCX, and $i10CX$.

10.3.1.1 Example of CCR and CCX

To get a glimpse of these indicators' behaviour we selected four scientists from one of our datasets, which will be presented in detail in Sect. 10.4.1. Table 10.2 displays the names of these scientists from the list of 219 Greek prolific authors. Georgios Giannakis (GG) is the most highly cited; Christos Davatzikos (CD) occupies a middle position, whereas Iakovos Venieris (IV) and Agathoniki Trigoni (NT) have a modest position of all scientists with more than 150 publications in this list.

Table 10.3 displays year-wise citations c of these four scientists. For each scientist, at each instant, c is the proxy for current citation impact. For each scientist, cumulative citations C can be computed as shown in Table 10.3, for the window up to this instant. Table 10.3 as well as Figs. 10.1-10.2 show how CCR and CCX indicators evolve for the four scientists, who are at noticeably different stages of their scientific career. A younger promising scientist, a rising star, tends to have a higher CCR. An older scientist who is a "fading" star will tend to lower CCR. Both c and C differ considerably, and this is compounded in the composite indicator CCX. These values can rise as for CD, or fall, rise and fall, as for GG and IV, as seen in Figs. 10.1 and 10.2. IV's CCR peaked in 2000 and CCX in 2002. In the case of GG, CCR peaked in 2005 and CCX in 2006.

Table 10.2 Four scientists from the list of prolific Greek scientists in the DPLB at different positions in the performance spectrum taken from Google Scholar Citations. Undefined variables will be clarified in Sect. 10.4.1

Author name	$\|\|P\|\|$	C	h	$i10$	C_5	h_5	$i10\_5$
Georgios Giannakis	972	77789	145	718	24863	76	412
Christos Davatzikos	282	45420	106	387	24293	72	311
Agathoniki Trigoni	166	5734	40	97	4063	33	78
Iakovos Venieris	166	3132	26	84	713	13	21

Table 10.3 Year-wise citations c since 1996 of the four scientists, computation of the cumulative citations C, the citation currency ratio CCR, and the citation currency exergy CCX

	CDavatzikos				IVenieris				GGiannakis				ATrigoni			
Year	c	C	CCR	CCX	c	C	CCR	CCX	c	C	CCR	CCX	c	C	CCR	CCX
1996					42	42	1.000	42.0	386	386	1.000	386.0				
1997					38	80	0.475	18.1	558	944	0.591	329.8				
1998	148	148	1	148	52	132	0.394	20.5	473	1417	0.334	157.9				
1999	186	334	0.55	103.58	37	169	0.219	8.1	566	1983	0.285	161.6				
2000	244	578	0.42	103.00	74	243	0.305	22.5	694	2677	0.259	179.9				
2001	281	859	0.32	91.92	96	339	0.283	27.2	877	3554	0.247	216.4				
2002	383	1242	0.30	118.10	128	467	0.274	35.1	1160	4714	0.246	285.4				
2003	446	1688	0.26	117.84	134	601	0.223	29.9	1522	6236	0.244	371.5				
2004	594	2282	0.25	154.61	160	761	0.210	33.6	2245	8481	0.265	594.3				
2005	762	3044	0.21	190.75	156	917	0.170	26.5	3108	11589	0.268	833.5	33	33	1	33.0
2006	852	3896	0.21	186.32	150	1076	0.141	21.1	3831	15420	0.248	951.8	70	103	0.679	47.5
2007	1048	4944	0.19	222.15	183	1250	0.146	26.8	4222	19642	0.215	907.5	80	183	0.437	34.9
2008	1174	6118	0.18	225.28	145	1395	0.104	15.1	4543	24185	0.188	853.4	84	267	0.314	26.4
2009	1401	7519	0.16	261.04	168	1563	0.107	18.1	4391	28576	0.154	674.7	129	396	0.325	42.0
2010	1463	8982	0.17	238.29	148	1711	0.086	12.8	4447	33023	0.135	598.8	166	562	0.295	49.0
2011	1868	10850	0.15	321.60	143	1854	0.077	11.0	4165	37188	0.112	466.5	158	720	0.219	34.6
2012	2008	12858	0.14	313.58	134	1988	0.067	9.0	4321	41509	0.104	449.8	202	922	0.219	44.2
2013	2133	14991	0.14	303.49	159	2147	0.074	11.8	4549	46058	0.099	449.3	207	1129	0.183	37.9
2014	2553	17544	0.13	371.51	137	2284	0.060	8.2	4738	50796	0.093	441.9	261	1390	0.187	49.0
2015	2852	20396	0.14	398.78	128	2412	0.053	6.8	4106	54902	0.075	307.1	399	1789	0.223	88.9
2016	3522	23918	0.14	518.62	107	2519	0.042	4.5	4374	59276	0.074	322.8	335	2124	0.157	52.8
2017	4035	27953	0.14	582.45	126	2645	0.048	6.0	4255	63531	0.067	285.0	452	2576	0.175	79.3
2018	4658	32611	0.14	665.32	127	2772	0.046	5.8	4219	67750	0.062	262.7	720	3296	0.218	157.2
2019	5476	38087	0.14	787.31	130	2902	0.045	5.8	4305	72055	0.060	257.2	1100	4396	0.250	275.2

10.4 Case Studies of Greek and Indian Scientists

In this section we will first present in detail the datasets we have collected over which we will evaluate the appropriateness of the proposed indicators, and then we will show the actual experimental results.

10.4.1 Datasets Collection and Measured Indicators

To showcase the usefulness of the proposed indicators, we created two datasets; one with scientists with Greek origin and the second with Indian scientists. The first dataset is curated by identifying the prolific authors from DBLP[2] which have Greek last names. They can be citizens of Greece, of Cyprus, or of any other country such as USA, UK, Australia, or elsewhere, affiliated with any academic or research institution in Greece, Cyprus and so on. They all have a record of at least 150 publications according to DBLP. In passing, publications according to DBLP can be journal or conference papers, as well as books edited or authored, technical reports

[2] https://dblp.org/statistics/prolific1.html

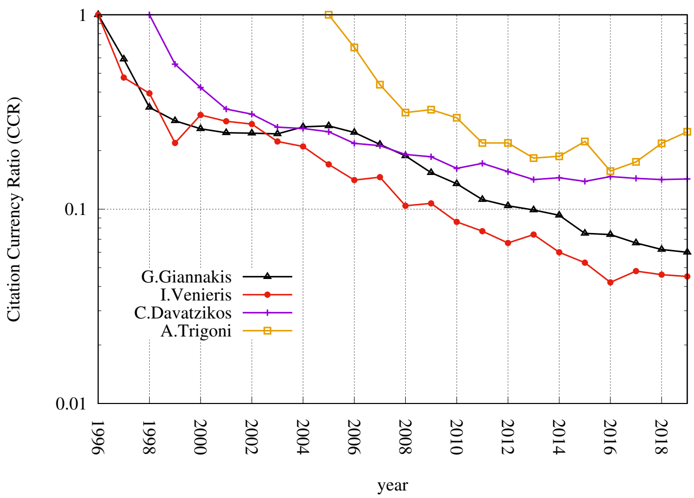

Fig. 10.1 Evolution of CCRs of four sampled Greek scientists

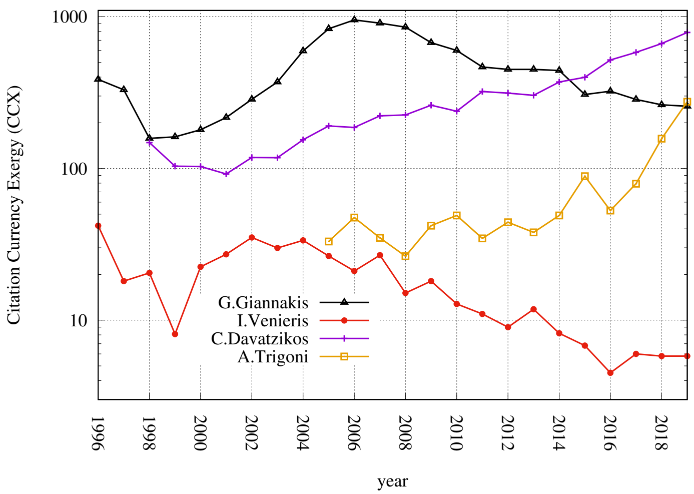

Fig. 10.2 Evolution of CCXs of four sampled Greek scientists

etc[3]. For each author of this set, we checked their profile in Google Scholar (GS). Those without GS profiles were removed from further consideration, and, thus, a

[3] We mention that these "publications" contain many CoRR articles, which comprise unreferred works uploaded to arxiv.org. In recent years this duplication of articles in DBLP is quite significant, accounting for some authors even to 20% of their total number of publications.

set of 219 prolific Greek researchers has been gathered (curation date: the 17th of December 2020)[4].

For each GS profile, we can retrieve the citations in all years (C) to all publications (P), and also a so-called "recent" value of this metric (C_5), which is the number of citations to all publications in the past five years. Also, we can get the well-known h-index [7], the so-called h_5, which is the h-index which is the largest number h such that h publications in the past five years have at least h citations. The $i10$-index is the number of publications which have at least 10 citations, whereas $i10\_5$ is the corresponding value for the last 5 years.

The second dataset uses the Indian academic space as an example. The latest Stanford list [8], gives two separate lists which cover the cumulative and "recent" windows. The citation data from Scopus is frozen as of May 6, 2020. The Single Year list (Table-S7-singleyr-2019) gives the citation impact, nc1919(ns) during the single calendar year 2019 for more than 160000 scientists from a ranking list of more than 6 million scientists. This corresponds to the "recent" citation value c for our calculations. The Career list (Table-S6-career-2019) assesses scientists for career-long citation impact, nc9619(ns) from 1996 until the end of 2019 for nearly 160000 scientists from a ranking list of nearly 3 million scientists. This corresponds to our cumulative citations C from 1996 to 2019. The qualifier (ns) indicates that self-citations have been excluded. From this, the citation currency ratio CCR and the citation currency exergy CCX can be computed for every scientist who appears simultaneously in both lists. The Single Year list gives many rising stars (i.e., they are here but absent in the Career list). Similarly, from the Career list, we can also see the fading (sinking) stars, where they are absent from the Single Year list. Many names remain common to both lists, and it is only for this cohort that we can compute CCR and CCX. All updated databases and code are made freely available in Mendeley[5].

We will focus our attention only on the names from India's premier research intensive Higher Educational Institution, namely the Indian Institute of Science at Bengaluru, India which appear in the Stanford list [8]. There are 97 scientists in the Single Year list, 94 in the Career list and only 65 in the common list. It is this last cohort which we shall use to continue our demonstration. Table 10.4 is an extract showing the top-20 scientists from the Indian Institute of Science, Bengaluru, India from the so-called Stanford list [8]. The actual names are shown as they offer a reality check and there are no surprises. The Stanford list also makes available for each scientist the respective year of first publication (firstyr) and year of most recent publication (lastyr). We shall use this to show how the citation indicators evolve with year of first publication, which we take as the date of launch of the scientific career.

[4] The dataset is publicly available upon request.

[5] https://dx.doi.org/10.17632/btchxktzyw

Table 10.4 The top 20 scientists from the Indian Institute of Science, Bengaluru, India from the so-called Stanford list [8]

Author name	firstyr	lastyr	c	C	CCR	CCX
Desiraju, Gautam R.	1977	2020	3098	34086	0.091	281.57
Sood, A. K.	1979	2020	2035	15555	0.131	266.23
Ramaswamy, Sriram	1979	2020	1097	7133	0.154	168.71
Sarma, D. D.	1980	2020	1420	12662	0.112	159.25
Munichandraiah, N.	1981	2019	1118	7432	0.150	168.18
Raj, Baldev	1982	2018	1591	10199	0.156	248.19
Gopakumar, K.	1984	2020	1183	7163	0.165	195.38
Sitharam, T. G.	1987	2020	612	2390	0.256	156.71
Ghose, Debasish	1988	2019	826	4506	0.183	151.42
Shivakumara, C.	1991	2020	757	3719	0.204	154.09
Ramachandra, T. V.	1992	2020	667	2744	0.243	162.13
Madras, Giridhar	1993	2020	2435	14247	0.171	416.17
Nanda, Karuna Kar	1994	2020	819	4000	0.205	167.69
Kumar, Jyant	1994	2020	561	1916	0.293	164.26
Suwas, Satyam	1996	2020	1173	3820	0.307	360.19
Somasundaram, Kumaravel	1996	2019	1053	5995	0.176	184.9 6
Basu, Bikramjit	1998	2020	1437	6398	0.225	322.7
Mukherjee, Partha Sarathi	2000	2020	1334	8657	0.154	205.56
Biju, Akkattu T.	2003	2020	970	5042	0.192	186.61
Barpanda, Prabeer	2004	2020	717	2971	0.241	173.04

10.4.2 Case Study 1: Application of the New Indicators to Prolific Greek Scientists

Using the dataset with the prolific Greek scientists, we aim to show the dynamics of their profile by means of currency indicators. In particular, we will calculate the dimensionless *citation currency ratio (CCR)* and a size-dependent citation currency exergy (CCX) to capture these trends quantitatively.

Figs. 10.3-10.5 show the dispersion of currency ratios CCR, hCR and $i10R$ and the respective values of C, h, and $i10$ for the 219 Greek prolific authors. Logarithmic scales are used and in each case the power trendlines are shown. We clearly see that in the case of citations and the h-index, at higher levels of C and h, indicating mature scientists, the CCR goes down perceptibly. However, such a signal is not evident in the case of the $i10$-index for reasons still under examination. We also see that in all cases, there is little correlation.

10.4.3 Case Study 2: Application of the New Indicators to Prolific Indian Scientists

Using the second dataset, namely with the Indian scientists we explore the usefulness of our proposed indicators. Fig. 10.6 shows the evolution of the citation currency ratio CCR for the 65 scientists from the Indian Institute of Science, Bengaluru, India from the Stanford list [8]. The exponential law trendline shows that younger scientists (by scientific age) have higher CCR. The egregious outlier seen in the figure is that of G.N. Ramachandran, whose scientific career spanned from 1942 to 1994 with

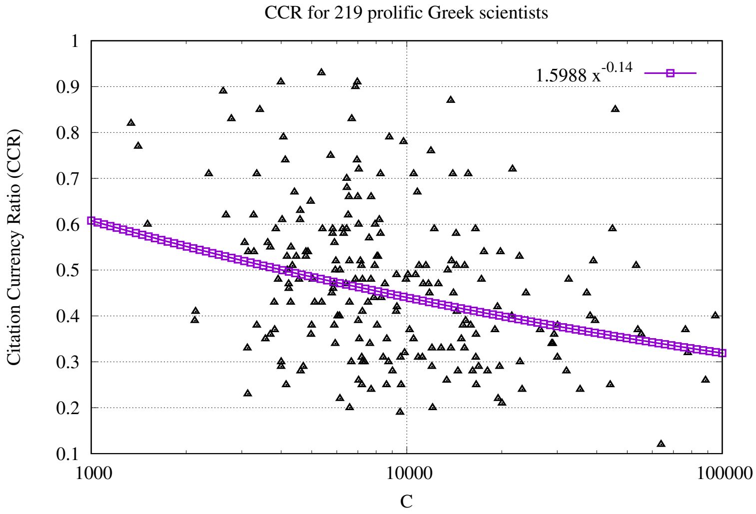

Fig. 10.3 The dispersion of CCR and the total citations C for the 219 prolific Greek scientists

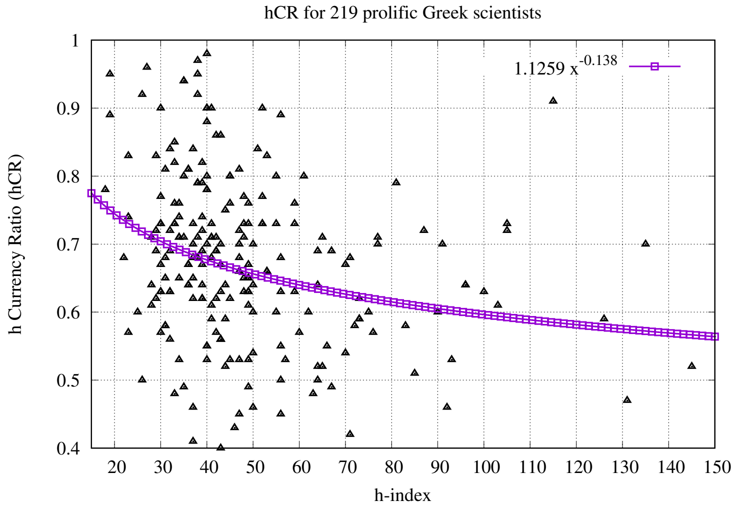

Fig. 10.4 The dispersion of Currency Ratio hCR and the h-index for the 219 prolific Greek scientists

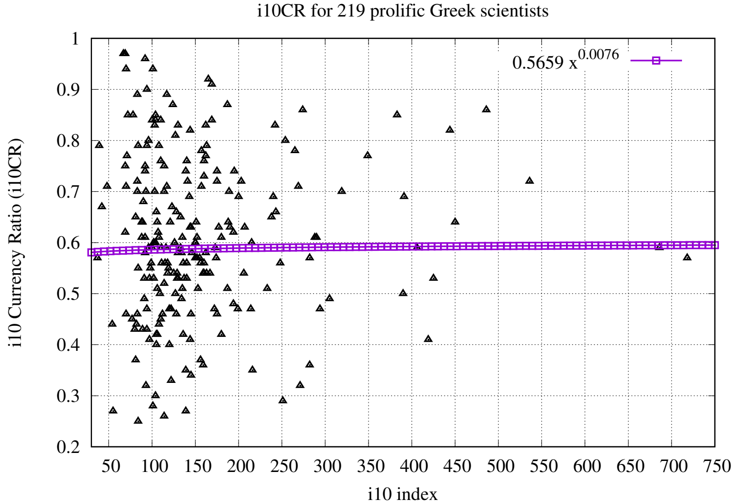

Fig. 10.5 The dispersion of Currency Ratio $i10CR$ and the $i10$-index for the 219 prolific Greek scientists

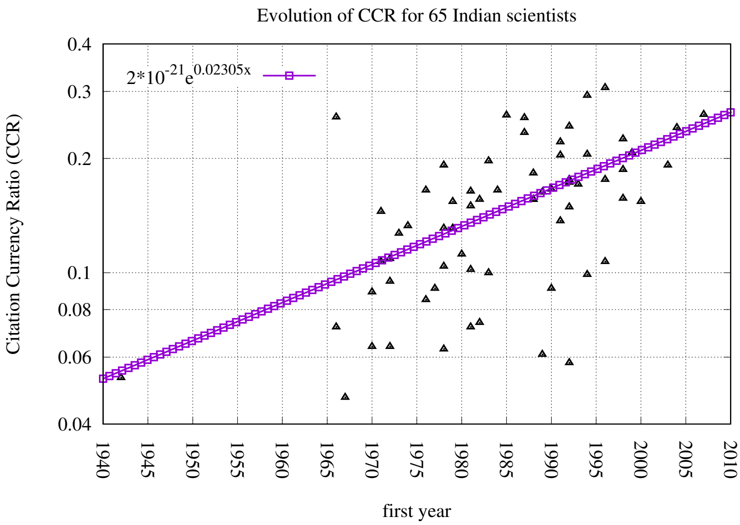

Fig. 10.6 The evolution of the Citation Currency Ratio CCR for the 65 scientists from the Indian Institute of Science, Bengaluru, India from the Stanford list. The powerlaw trendline shows that younger scientists (by scientific age) have higher CCRs

$c = 330, C = 6233, CCR = 0.053$, and $CCX = 17.47$. Twenty-five years on, his scientific legacy continues to attract citations.[6]

[6] Many in India believe that he was very unfortunately overlooked for a Nobel Prize.

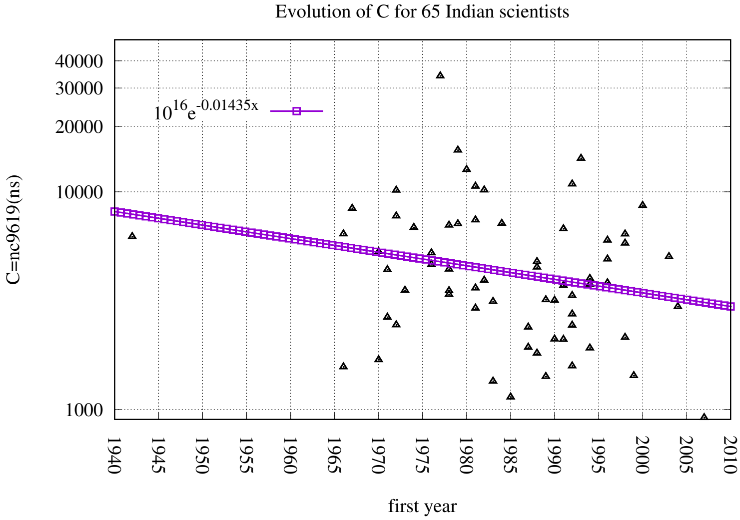

Fig. 10.7 The evolution of the size-dependent cumulative citations C for the 65 scientists from the Indian Institute of Science, Bengaluru, India from the Stanford list. The exponential law trendline shows that younger scientists (by scientific age) have lower cumulative citations C

Fig. 10.7 shows the evolution of the size-dependent cumulative citations, C for the 65 scientists. The exponential law trendline shows that younger scientists (by scientific age) have lower cumulative citations C. The highest performer here is Gautam R. Desiraju, with a career spanning from 1977 to 2020 and with $c = 3098$, $C = 34086$, $CCR = 0.091$, and $CCX = 281.57$.

Fig. 10.8 shows the evolution of the composite size-dependent cumulative citation currency exergy CCX for the 65 scientists. The exponential law trendline shows that younger scientists (by scientific age) have higher citation currency exergies CCX. The highest-ranking performer by this criterion is Giridhar Madras, with career spanning from 1993 to 2020, and $c = 2435$, $C = 14247$, $CCR = 0.171$, and $CCX = 416.17$. This is an excellent illustration of how current and cumulative activity go strongly together at this prime stage of a career.

Fig. 10.9 shows the dispersion of CCR with $C = nc9619(ns)$ for the cohort of 65 scientists. The power law trendline shows that there is a negative slope and correlation with C. This is to be expected from what we have seen earlier. Younger scientists have lower C and higher CCR but higher citation currency exergies CCX. The older scientists slowly fade away. G. N. Ramachandran remains an exception while many doyens of science from India of his era have now vanished from the Single Year lists.

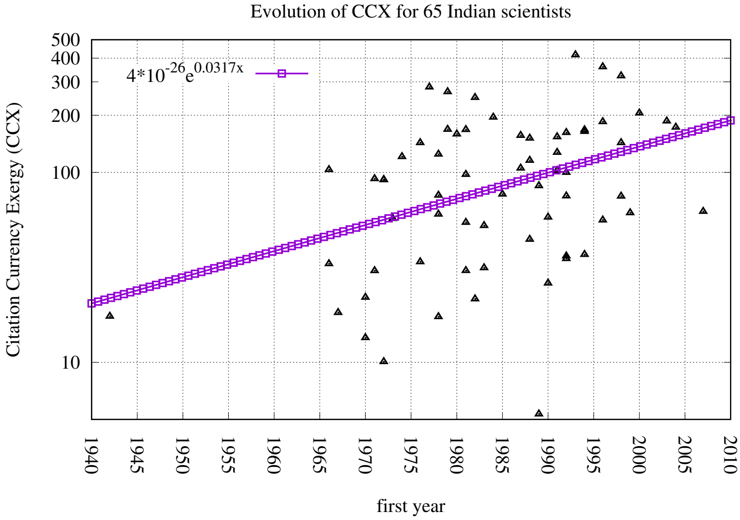

Fig. 10.8 The evolution of the composite size-dependent cumulative citation currency CCX for the 65 scientists from the Indian Institute of Science, Bengaluru, India from the Stanford list. The exponential law trendline shows that younger scientists (by scientific age) have higher citation currency exergies CCX

10.5 Concluding Remarks

Most scientists are active over long periods. Some are younger and some are at the end of their careers. The old truism about soldiers is valid: old scientists never die; their impact in terms of citations just fade away. In this paper we introduced two new indicators, a dimensionless *Citation Currency Ratio* (CCR) and a size-dependent *Citation Currency Exergy* (CCX) to capture these stages quantitatively. A welcome feature of CCR is that it starts from a value of 1 and never exceeds this and diminishes to zero as the portfolio fades away. Thus, at the very beginning of a scientific career one would start with a CCR value of 1 and at the very end, only when the portfolio of work ceases to gather citations, and not when the agent stops work, it becomes zero. We saw this in the case of G. N. Ramachandran, whose scientific career spanned from 1942 to 1994, that twenty-five years on, his scientific legacy continues to attract citations. We study cohorts of scientists to see how this happens across the board. We use data from DPLB and Google Scholar as well as another recently published dataset, the Stanford list [8], demonstrate the applicability of these ideas. These help to identify scientists who are at different stages of their career, with rising, steady, or fading visibility.

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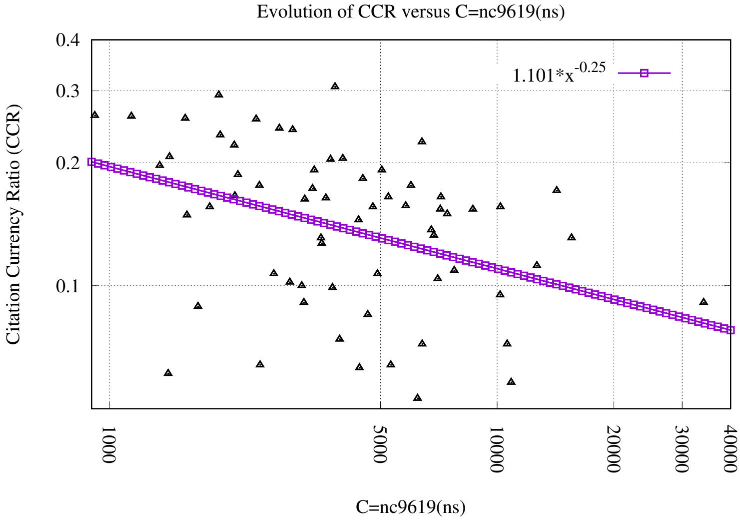

Fig. 10.9 The scatter plot of the dispersion of CCR with $C = nc9619(ns)$ for the 65 scientists from the Indian Institute of Science, Bengaluru, India from the Stanford list. The power law trendline shows that there is a negative slope and correlation with C. This is to be expected from what we have seen earlier. Younger scientists (by scientific age) have lower C and higher CCR, but higher citation currency exergies CCX

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