[1]Elias Kapambwe

[2] Bessie, B. Monchusi,

Solar Cell Parameters Extraction Methods: A Bibliometric Analysis Review

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Abstract: - This paper presents a bibliometric analysis review of solar cell parameters extraction methods. The paper focuses on trends in publications, identifying possible knowledge gaps and future potential research direction regarding improvement in solar cell parameters extraction methods. In order to achieve this objective, a total of 300 Journal articles published from 2015 to 2023 inclusive were retrieved from the Dimensions database on this subject. After screening the articles by title, 224 were included in the analysis. Taking into account, among other metrics; publications, citation, location in the network, recent and relevance with the subject matter under study, countries which have collaborated most in document publication were identified. The study also revealed authors who are deemed to be influential in this field as well as highly ranked documents and institutions. The key words that may suggest further investigation in order to address the subject of solar cell parameters extraction methods were also identified. Additionally, other research gaps that may suggest possible study direction such as underrepresented areas were recognized.

Keywords: Bibliometric Analysis, Five Parameter Model, Parameters Extraction Methods, Solar Cell.

I. INTRODUCTION AND BACKGROUND LITERATURE

The current-voltage (I-V) characteristic of any solar photovoltaic (PV) module is the key factor in identifying the quality and performance of the PV solar cell as a function of varying environmental parameters such as solar irradiance and ambient temperature [1]. Furthermore, the PV and IV curves indicate the characteristic parameters of the PV generator represented in short circuit current, open circuit voltage and point of maximum power at which the generator would work at its peak efficiency. These parameters are useful in designing PV power systems and determine the equivalent circuit components of the PV generator which are represented by the series and shunt resistance [1], and which are disclosure parameters for classifying the quality of the generator substrate material. In order to predict the performance of real solar cells or modules in outdoor environment, and at the same time obtain the current-voltage characteristic, modeling of a solar cell is important. Accurate modeling is vital for solar PV systems, as the parameter extraction of photovoltaic models significantly affects the efficiency of the conversion of solar energy to electricity [2]. Accurate parameter extraction of photovoltaic models is considered a critical issue for optimization, simulation, and evaluation of PV energy systems. The authors in [3] have indicated that solar PV modules show a non-linear I-V characteristic with several parameters that need adjustment during experimental data analysis of practical modules. Although the values of some of the parameters are provided in the manufacturer's datasheet, the values of unknown parameters, such as shunt resistance, series resistance, the diode ideality factor, photo generated current and diode saturation current, are not provided [4]. Thus, modeling ensures accurate representation of non-linear characteristics of PV systems, and is the key factor that affects the accuracy of the simulation [5]. Simulation and emulation of PV cells is crucial for energy yield prediction, quality control during manufacturing [6] and for the study of PV cell degradation.

The I-V curve provides a lot of information and important characteristics that are useful for testing, measuring and modeling the performance of PV systems. Researchers have dealt with the measurement of I-V characteristic curves of PV modules under different operating conditions using a variety of parametric models. Authors in [6] have indicated two methods of measuring I-V curves; the online and offline methods. The online method uses elements such as resistors, capacitors and switches to measure the specifications of the PV cell while the offline methods are mainly based on generic algorithms and artificial intelligence [6]. However, [6] have pointed out some drawbacks about the online methods such as inaccuracy, time constraints and the inability to use them in large-scale systems.

A solar PV cell is described by an equivalent electric circuit consisting of a current source, at least one diode, and one resistor which is based on the cell's intrinsic characteristics [7]. Common PV equivalent electric circuits are those for single-diode model (SDM), double-diode model(DDM) and triple-diode model (TDM). Each of these models has particular advantages and disadvantages. Authors in [8] like many other researchers have singled out SDM and DDM as being the most commonly used models because they provide better relations with a practical solar cell and are simple. The researchers have based their arguments on the fact that these two models are fast in

[1]Department of Electrical Engineering, University of South Africa, 0001; email: kapambwe1965@gmail.com

[2] Department of Electrical Engineering, University of South Africa, 0001

extracting cell parameters and that the I-V and power-voltage (P-V) characteristic curves produced by the two models give minimum error with respect to characteristics of the solar PV cell. However, in making comparisons between SDM and DDM, the authors are of the view that the SDM gives much more acceptable results in various conditions within less iteration as demonstrated using a flow chart in MATLAB for a typical BP solarex MSX-120 W solar panel. The authors further recommend that the SDM is the most suitable model which can be used for simulating electrical behavior of PV module systems for planning purposes in the field of power system.

Different researchers have different opinions over the use of SDM and DDM. The fact that the SDM does not take into consideration the recombination losses in the depletion region, some researchers such as [9] do not consider this model to be accurate. The observation made by these researchers is that the DDM gives much more accurate results compared to the SDM which suffers from inaccuracy when exposed to weather changing conditions and this makes it impracticable for real life implementation. However, the two unknown diode ideality factors introduced in the DDM increases the number of equations and this makes calculations complex. This observation is supported by [7] who allude to the fact that though the DDM model has certain advantages in representing the recombination loss in the depletion region, the model requires solving implicit non-linear seven-parameter equations which can lead to more difficulties in the calculation of the initial values, long computational time, and algorithm complexity. Authors in [9] are of the same opinion that although the DDM takes into account the diffusion and recombination of the minority carriers phenomena in the PV solar cell, the increased number of unknown parameters also increases complexity. The authors are also of the view that although the DDM is more accurate at low voltages under dark conditions, where the current is very small; at maximum power point the voltage is sufficiently high such that the photocurrent dominates and so the effect of the second diode, the one related to the recombination of minority carriers can be neglected.

Authors in [10] insist on implementing the (SDM) as PV equivalent electric circuit because it adequately fits with the I-V characteristic at Standard Testing Conditions (STC) of most modern and efficient PV modules, which, because of having a small series resistance and large shunt resistance, show a good fill factor and, consequently, an I-V characteristic with a sharp bend. On the application of the DDM, the authors in [10] like many other researchers, assert that the DDM requires the determination of seven parameters that variously affect the shape of the I-V characteristic, in particular, the series resistance and shunt resistance change the slope of the I-V curve, before and after the “knee”, respectively, while the ratio between the reverse saturation current tends to modify the curvature. The authors in [10] further agree that although it is not a problem that is mathematically indeterminate, the calculation of the seven parameters, however, is not easy considering the implicit form of the equation and the presence of two exponential terms.

Moreover, the researchers who tend to favor the DDM based on producing accurate results at lower values of irradiance and temperature, do not take into account environments such as those in tropical regions where there are no extreme variations in irradiance and temperature. For example, [6] have indicated that solar radiation in tropical region of Malaysia is stable and does not change significantly throughout the year. Table I shows how solar irradiance varies in selected districts in tropical region of Zambia over a period of one year. From the table it can be easily seen that solar irradiance is more or less constant throughout the year.

Table I. Variation in irradiance (kWh/m2/day) over selected districts in Zambia [11]
L/ngwa = Luangwa; M/nilunga = Mwinilunga; L/ka = Lusaka; L/stone = Livingstone

Month	Kaputa	L/ngwa	M/nilunga	Ndola	Chipata	Zambezi	L/ka	L/stone
Jan	4.9	5.38	4.14	5.45	5.54	5.20	5.76	6.19
Feb	5.22	5.52	4.33	5.42	5.56	5.33	5.73	6.21
March	5.44	5.56	4.42	5.83	5.83	5.52	6.11	6.44
April	5.78	5.40	5.28	6.28	6.13	6.04	6.21	6.26
May	6.09	5.19	5.36	5.90	5.70	5.89	5.68	5.66
June	6.02	4.76	5.33	5.56	5.21	5.72	5.22	5.26
July	6.13	4.99	5.50	5.82	5.34	6.01	5.44	5.45
Aug	6.48	5.85	5.78	6.44	6.00	6.36	6.23	6.16
Sept	6.32	6.51	5.83	6.98	6.65	6.44	6.90	6.87
Oct	5.73	6.73	5.42	7.16	7.21	6.18	7.20	7.05
Nov	5.08	6.35	4.50	6.27	6.42	5.67	6.54	6.57
Dec	4.9	5.47	4.14	5.50	5.79	5.31	5.94	6.14
Year	**5.68**	**5.64**	**5.01**	**6.05**	**5.95**	**5.81**	**6.09**	**6.19**

Although [12] have agreed that the SDM suffers from inaccuracy when exposed to weather changing conditions, the authors have, however, like many other researchers, found it to be useful because of its simplicity and less number of unknown parameters which makes it easier to analyze and extract the unknown parameters from it. [12] have also based their arguments on the SDM's inaccuracy on variation conditions in temperature and irradiance. This means that the SDM might equally perform well in environments where the temperature and irradiance do not vary significantly as the case is in regions with tropical climate. Therefore, considering its simplicity and less computational errors, [8] have strongly recommended the SDM as one which gives acceptable results in various conditions with less iteration and that it is the most suitable model which can be used for simulating electrical behavior of PV module systems for planning purposes in the field of power system.

[13] and [7] have supported the idea of adopting the five-parameters SDM for the equivalent electric circuit because of its good comprise between precision and simplicity. [14] have echoed the same positive sentiments concerning the SDM that due to its simplicity, accuracy and reliability, it is commonly used in practice for modelling and simulation purposes and that for certain cases, the performance of SDM is found to be satisfactory, even after neglecting recombination losses existing in the diode. However, [15] agree that the inclusion of a second diode to form a DDM and another extra diode to form a (TDM) in order to take into account the recombination losses improves modeling performance and accuracy of these models but at the cost of increased complexity. [15] have also expressed similar concerns about DDM and TDM that although complex extraction procedures required by these models can produce high precision parameter values, the computational process may lead to inefficiency.

PV technologies which have so far reached maturity can be divided into three categories; mono-crystalline, poly-crystalline and thin film. These technologies rely on PV effect in silicon p-n junction [5] and so their behavior can be modeled using an equivalent electric diode circuit with different components where each is representative of a certain physical mechanism within the cell such as cell bulk resistance and excitons recombination. However, the values of these parameters are not available in the manufacturers' technical data sheets [5]. Even the values of open-circuit voltage, short circuit current and maximum power which the manufacturers usually provide are simply reflective of the standard testing conditions of irradiance 1000 W/m2, temperature 25^{o} C and Air Mass 1.5 which are far from the real operating conditions. For this reason, real-time fast parameter extraction is necessary [5]. The extraction of the PV model parameters remains to this day a long-standing and popular research topic [16].

For parameter extraction of the model, [5] distinguish two main approaches. The first one is the analytical approach which is based on information from several key points on the I-V curve such as short-circuit current, open circuit voltage, maximum power point and the gradient of the curve. Although this approach is relatively simple and the calculation process fast, the simplification and replacement of key parts of the equation to calculate the parameter values often lead to lack of accuracy and to results without physical significance [17]. The authors in [17] further add that the fact that the parameters are obtained from the data in the manufacturers' datasheet, results obtained are also sensitive to measurement errors which can be caused by different accuracy of test equipment.

The other approach or category is numerical methods which allow for the usage of deterministic and stochastic optimization algorithms. Numerical analysis is needed to obtain the roots of transcendental equations i.e. equations containing trigonometric functions, exponential functions or logarithmic functions [18] and is based on the accuracy of the error reached. These processes can minimize the errors between the obtained I-V and P-V characteristic and the experimental data, and then obtain high-precision parameter values [17]. However, according to [17], the inefficiency of the calculation process has always been the biggest problem for this kind of extraction process.

Depending on the nature of the roots obtained, [7] have identified the following numerical techniques; the Newton Raphson method, Iterative curve-fitting method, Conductivity method, Levenberg Marquardt method among others as falling under the deterministic algorithm while generic algorithm method, the particle swarm optimization method and artificial bee swarm optimization method among others fall under stochastic methods. [15] have also included under numerical techniques, the Bisection method, and False Position method.

The purpose of this paper is to review research done on solar cell parameters extraction methods using the science of mapping review technology. The review addresses the following research questions (RQs):

RQ1: What is the current trend of publication on solar cell parameters extraction methods?

RQ2: Which authors and documents in the literature on solar cell parameters extraction methods have had the greatest impact in the period 2015 to 2023?

RQ3: What are the key concepts that have been explored on solar cell parameter extraction methods?

RQ4: What is the nature of collaboration that is evident in the publications on solar cell parameters extraction methods?

RQ5: Which area (s) about solar cell parameters extraction methods may require further investigation?

II. METHODOLOGY.

To address the research questions stated in section I, a structured literature review of solar cell parameters extraction methods using bibliometric analysis is presented. Bibliometric analysis is a field which analyses and measures the impact of research output by using quantitative methods [18]. Bibliometric methods play an increasing role in ranking of research departments and institutions [19]. Bibliometric methods are also used to determine the potential strength and weaknesses that a given field of study may have from an objective point of view [20]. With the advent of scientific data bases such as Web of Science, Scopus, PubMed, Cross ref, Dimensions, Google scholar etc., acquiring large datasets has become relatively easy. To analyze such big volumes of data, software such as VOSviewer, UCINET, SciMat, Bibexcel, Gephi, Leximancer [21] and Harzing's Publish or Perish have been developed. Bibliometric can be used to analyze a number of metrics such as publications and citations of an individual researcher, a research group, an institution, a country or a research area. Further, bibliometric studies that are well done can build firm foundations for advancing a field in novel meaningful ways. Bibliometric analyses enable and empower scholars to (i) gain a one-stop overview (ii) identify knowledge gaps (iii) derive novel ideas for investigating and (iv) position their contributions to the given field [21]. Table II is a summary of some of the metrics that can be measured using bibliometric.

Table II. Bibliometric indicators [[18]

Metric	What it measures
Total publications	Total number of research output e.g. articles, books, book chapter, reviews, conference paper etc.
Citations	Average number of citations to a set of publications
Citation per publication	Average number of times a set of research output has been cited
Journal impact	Number of citations received in a calendar year to documents published in that Journal in preceding years
Cite score	Citations received in a calendar year to documents published in that Journal in preceding years e.g. three years in case of Scopus
SCImago Institute of Rankings (SIR)	Weighted citations received in year X to documents published in the Journal in year X-1, X-2 and X-3-=; SCIMAGO
Field-weighted citation impact (FWCI)	This is an indicator of mean citation impact and compares the actual number of citations received by a document with the expected number of citations for documents of the same document type (e.g. article, review, book, conference proceedings), publication year and subject area

A. *Bibliometric Analysis Research Design*

Bibliometric analysis has become a popular and rigorous method for analyzing large volumes of scientific data. Many researchers are turning to using bibliometric to analyze large volumes of data in various disciplines including renewable energy. For example, [22] applied bibliometric in the advancement of solar energy research. [23] applied bibliometric in the study of renewable energy and solar panel literature through bibliometric position over three decades. [24] analyzed research trends on Quantum-Dot-Sensitized Solar Cells over two decades with the help of bibliometric and [25] used bibliometric to analyze solar power research from 1991 to 2010.

Unlike systematic literature review and meta-analyses studies, bibliometric analysis does not require the researcher to download the full content of the data to be analyzed. Secondly, bibliometric analysis relies upon quantitative techniques unlike systematic analysis that tend to rely on qualitative techniques which could be marred by interpretation bias from scholars across different academic backgrounds [21]. Although meta-analysis is also quantitative in nature and can also handle large volumes of data, meta-analysis, however, concentrates on summarizing empirical evidence by analyzing the direction and strength of effects and relationships among variables and so, it is useful in addressing open research questions with data that are close to definitive than reported in any single primary study [21]. On the contrary, bibliometric analysis summarizes the bibliometric and intellectual structure of a given field by analyzing social and structural relationships between different research constituents such as authors, countries, institutions or topics. Among the uses of bibliometric analysis include examining the growth and trends of research in a particular field, identifying research gaps and collaboration patterns in research among authors, organizations and /or countries. Evaluating scholarly scientific performance and impacts and predicting future research directions are the other uses of bibliometric analysis.

In addition, this analysis can contribute to the progress of science and technology in many ways by allowing analysts to analyze international collaborations, laying the academic foundation for the evaluation of new developments, identifying major scientific actors, and performing technology forecasting [26]. Fig. 2.1 below illustrates the steps followed in conducting bibliometric analysis of this literature review.

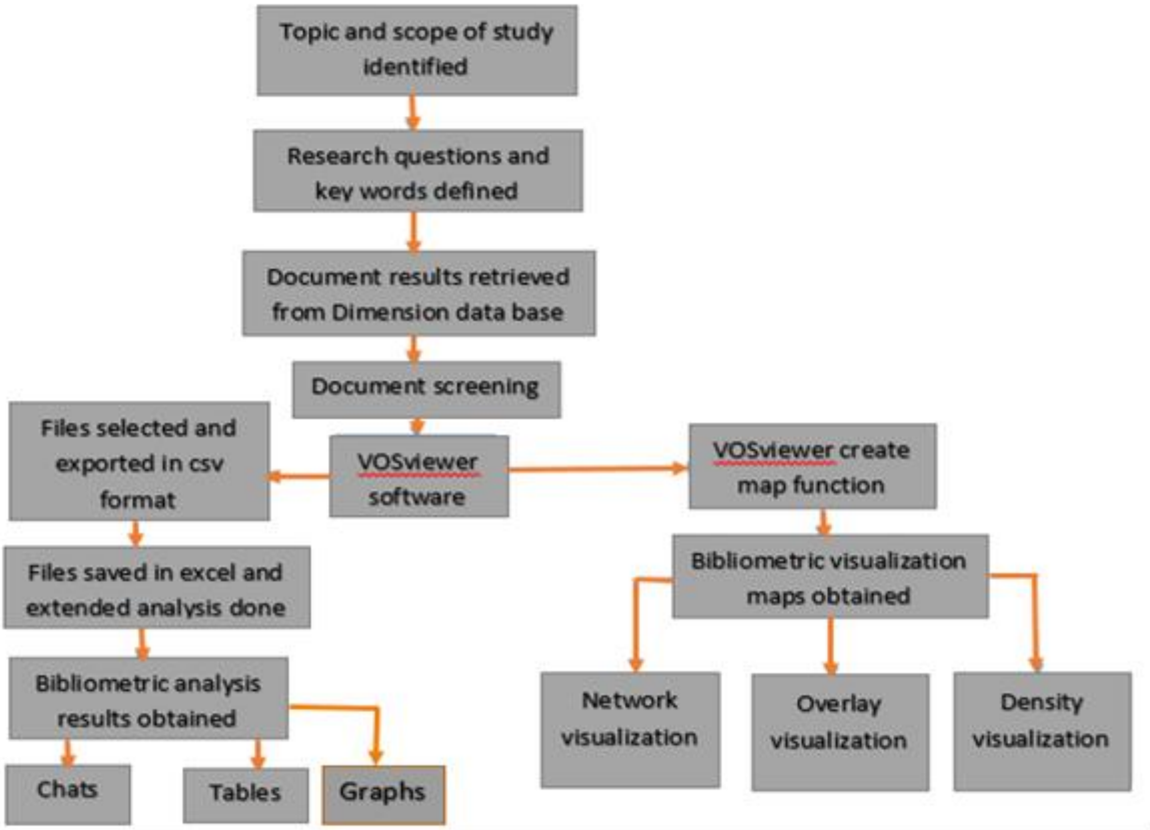


Figure. 2.1. Flow diagram for bibliometric analysis procedure

As per the flow chart in fig. 2.1, the first step in conducting this bibliometric analysis was to select the topic and the topic selected is ‘solar cell parameter extraction methods’ including analytical and numerical methods. The scope of review was restricted to publication years from 2015 to 2023 inclusive. The research questions to guide the bibliometric analysis were carefully formulated as indicated in section I. Table II shows the research questions and type of analyses used to address them. VOSviewer, version 1.6.19.0 [27] was used for bibliometric analysis. VOSviewer is a tool for constructing and visualizing bibliometric networks. The study of bibliometric using VOSviewer is recognized as a captivating method in the literature that allows examining the scientific progress of a particular topic [28]. A network is made up of actors. Actors can be people (e.g. authors) and/or organization groups that are tied by links. A network diagram such as the one shown in fig. 2.2 is a collection of entities. Entities are represented by nodes or vertices and linked by a type of relationship which is represented by edges or links.

Document search on solar cell parameters extraction methods was done in dimension database. The procedure followed in retrieving documents from the Dimensions database, screening and selecting those to include and exclude from the analysis is as shown in fig. 2.3. Dimensions is the world’s largest linked research database with 140 million publications; 29 million Datasets; 157 million Patents; 6 million Grants; 809 thousand clinical trials and 1 million Policy Documents [29]. The key words, “solar photovoltaic” OR “solar PV” AND “cell parameters” AND “extraction methods” were used to search documents in Dimension database. In the search strategy, documents were limited to those published from 2015 to 2023 inclusive. The search strategy was limited to document type, ‘articles’. With this search strategy, a total of 300 documents were retrieved. The documents were mainly screened by title and where the title was not very clear, the abstract was used to determine whether to include or exclude the document in the analysis. Thus, a total of 224 documents were finally included in the analysis. The flow chart shown in fig. 2.3 represents the process followed in retrieving documents from the Dimensions database as well as screening and selecting which document to include or exclude from analysis.

Table II. Science mapping technique used to answer research questions

RQ/N	Research Question	Science mapping technique used to answer RQ

RQ1	What is the current trend of publication on the methods used to extract solar cell parameters?	Co-authorship network: In these networks, researchers, research institutions or countries are linked to each other based on the number of publications they have co-authored. Co-authorship demonstrates collaboration between researchers or authors or between countries or between organizations.
RQ2	Which authors and documents in the literature on solar cell parameters extraction methods have had the greatest impact in the last 9 years?	Citation network: This network shows who has cited whom, and can be based on authors, documents, Journals, organizations or countries. Co-citation analysis: This network assumes publications that are cited together frequently and are thematically similar [30].
RQ3	What are the key concepts that have been explored on the subject of solar cell parameter extraction methods?	Co-occurrence networks: This science mapping technique is based on the number of co-occurrences of key words or terms that is the number of publications in which, say, 2 key words occur together either in the title, abstract or keyword list.
RQ4	What is the nature of collaboration that is evident in the publications on solar cell parameters extraction methods?	Co-authorship network: In these networks, researchers, research institutions or countries are linked to each other based on the number of publications they have co-authored. Co-authorship demonstrates collaboration between researchers or authors or between countries or between organizations.
RQ5	Which area (s) on the subject of solar cell parameters extraction methods may require further investigation?	Co-occurrence networks: This science mapping is based on the number of co-occurrences of key words or terms that is the number of publications in which, say, 2 key words occur together either in the title, abstract or keyword list. This science mapping technique can be used to identify areas in a given field that may need further investigation

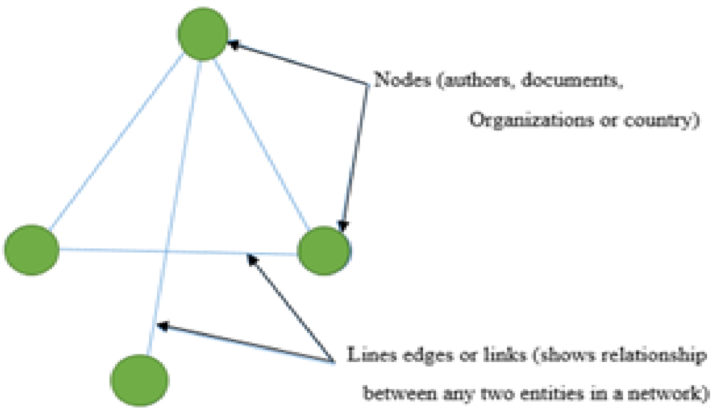


Figure. 2.2. Example of a network

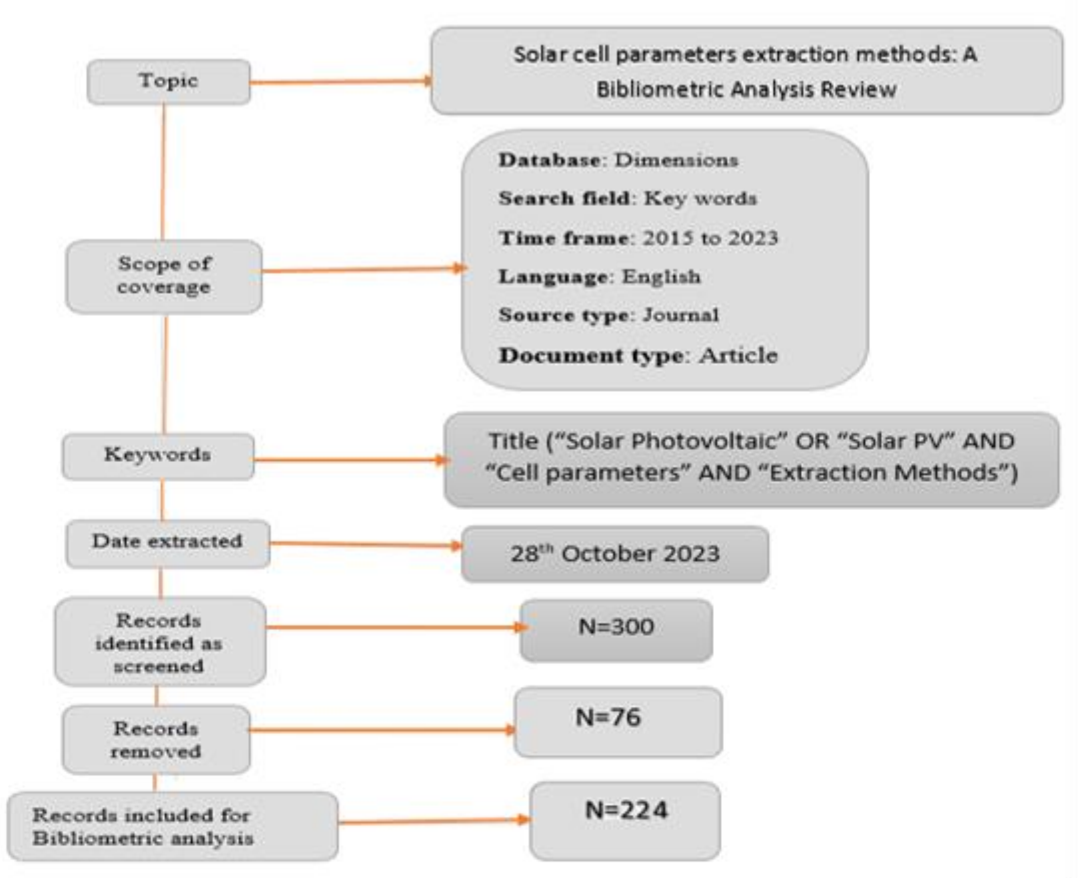


Figure 2.3. Flow chart used for the search and screening strategy

III. RESULTS AND DISCUSSION

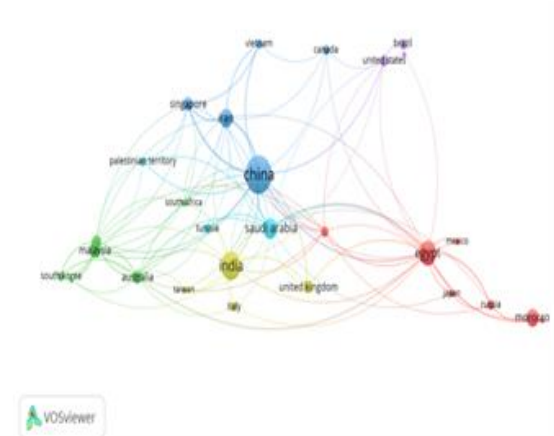
In this section results of the bibliometric analyses related to research questions highlighted in section I are presented. In analyzing bibliometric data, the author in [31] encourages the use of sense making which allows researchers to go beyond the mere description of data but develop interpretations that offer deeper insights into the data patterns, trends and implications. To utilize the sense making tool, [31] proposes three steps which should ensure the understanding of bibliometric results. The three steps are scanning, sensing and substantiating. Scanning involves locating clusters of related topics which could include theories, concepts, contexts and methods. Topics manifest as articles such as bibliographic coupling, co-citation analysis, citation analysis, co-authorship analysis and co-occurrence of key words analysis. Sensing involves interpreting data gathered during scanning process. According to the author in [31], during sensing the researcher should engage in a process of inquiry, developing an understanding of the "how" and "why" of the identified data patterns. Finally, in substantiating, the researcher establishes the trustworthiness of findings by confirmability, dependability, and transferability. So, in this analysis effort was made to follow these guidelines.

Research questions RQ1 and RQ4 were answered using the science mapping technique of co-authorship analysis. Co-authorship analysis examines the interactions among scholars in a research field. In co-authoring of documents, collaborations among scholars can lead to improvements in research. For example, contributions from different scholars can contribute to greater clarity and richer insight [32]. Co-authorship analysis can shed light on clustered research among scholars from a particular region and such insights can be used to justify and spark new research among scholars in underrepresented regions [21]. Here co-authorship analysis is used to analyze the data in terms of the publications and collaboration by country, organization and contributing author(s).

Co-authorship/country: In analyzing the data using VOSviewer, the maximum number of countries per document was set to 10 and minimum number of documents per country was set to 2. The number of citations per country was set to 1. With these settings 31 countries met the threshold out of 48. Of the 31 countries which met the threshold, 28 formed the largest set of connected countries. Fig 3.1 and 3.2 are screenshots of the network visualization and density visualization maps from VOSviewer showing the largest set of connected countries with a minimum of two documents and also countries which have collaborated most in research and publication on the subject of solar cell parameter extraction methods. In fig. 3.1 the size of the nodes indicates countries which have collaborated most with other countries in terms of research and publication on this subject. Here China leads followed by India and Egypt in collaboration in research and publication about solar cell parameter extraction methods with total link strength of 62, 24 and 40 respectively. A link is a connection or relation between two items [28]. In this case the items under consideration are the countries.

In the density visualization map of fig. 3.2, an item with bright yellow colour is one with the highest frequency [28]. In this case China, India and Egypt have bright yellow colour and so appear more frequently in terms of collaboration in research and publication with other countries on this subject. Other countries such as Malaysia, Morocco and Iran are also key players in this field. From fig.3.1 and 3.2, apart from South Africa, shown by a tiny node in fig. 3.1 and dull blue colour in fig. 3.2 indicating that its frequency is also very low, no other country in the Southern African region has either collaborated in publishing at least 2 documents or solely published any document on solar cell parameters extraction methods. This is an indication that there haven't been many studies going on this subject in this region.

Fig. 3.3 is a screenshot of the overlay visualization map from VOSviewer. On the map, colours indicate the impact countries have on document publication. In the overlay visualization map colours indicate scores. By default, [28] colours range from blue (lowest score) to green to yellow (highest score). The colour bar in right hand bottom shows how scores are mapped on to colours. It can be observed that United Arab Emirates (yellow dot next to Saudi Arabia), South Africa and South Korea produced documents which had great impact on document publication published between 2021 to 2022.



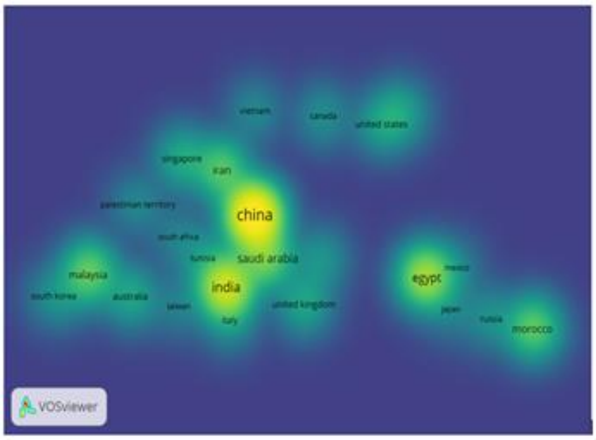


Figure 3.1. Network visualization map: co-authorship / country

Figure. 3.2. Density visualization map: co-authorship/country

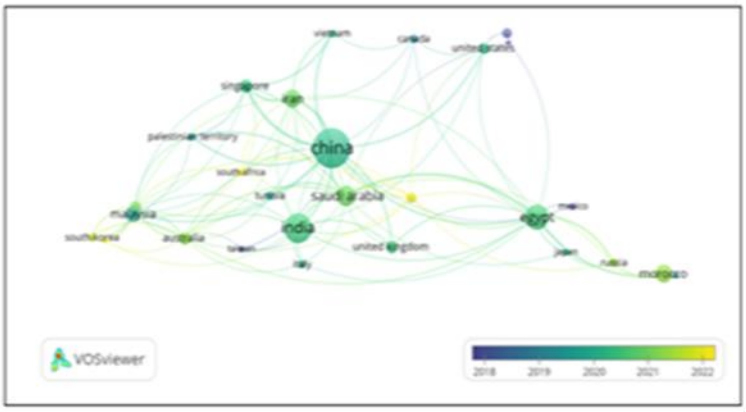
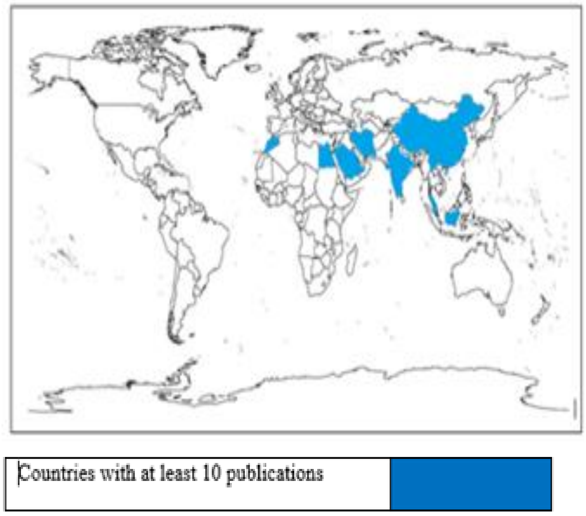


Figure 3.3. Overlay visualization map for co-authorship/country analysis

Fig. 3.4 shows the distribution of document publications on solar cell parameters extraction methods for countries with at least 10 publications. From the figure countries which have collaborated most in research and publication on solar cell parameters extraction methods are the Asian countries, the middle east and a few from north Africa. Fig. 3.5 shows countries in Africa which have collaborated in research and publication of at least two documents on solar cell parameters extraction methods. Here north Africa leads with a total of 54 publications. Of these, 32 publications are from Egypt, 17 from Morocco and 5 from Tunisia. Again, apart from South Africa with 3 publications, the entire Sub-Saharan African has not done any publication on solar cell parameters extraction methods at the time of reviewing.

Fig. 3.6 shows the number of publications per year from 2015 to 2023. The figure indicates an increase in the number of publications from 2015 to 2021. However, there was a slight decrease in the number of publications from 2021 to 2022. By 28th October 2023 only 30 documents had been published on solar cell parameters extraction methods in 2023. Fig. 3.7 is the cumulative document publications during the same period. The graph of fig. 3.7 shows a cumulative that increases almost exponentially in the number of publications from nearly zero in 2015 to around 200 in 2023. Such an increase can be attributed to continual research activities in this field especially in the wake of threatening global warming and climate change due to carbon dioxide emissions mainly coming from burning fossil fuels in fossil fueled power plants.



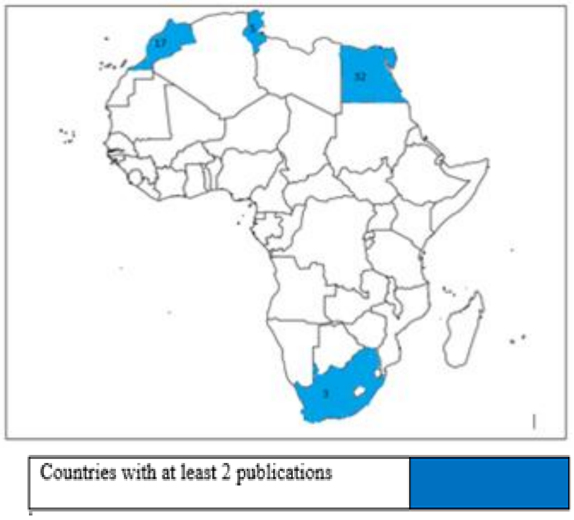


Figure.3.4. Worldwide distribution of document publications on solar cell parameters extraction methods

Figure. 3.5. Distribution of publications on solar cell parameters extraction methods in Africa

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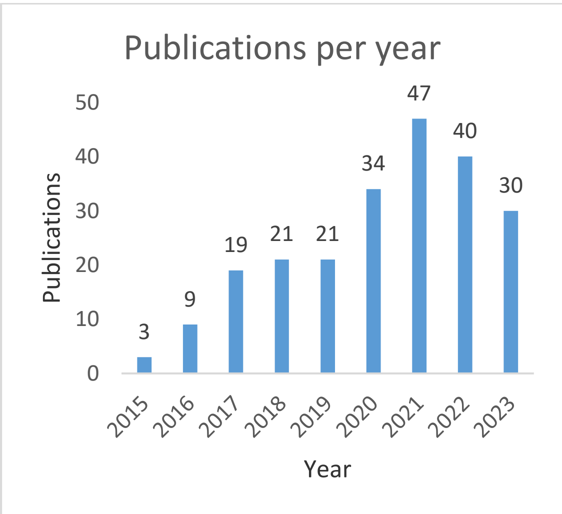


Figure. 3.6. Yearly document publications

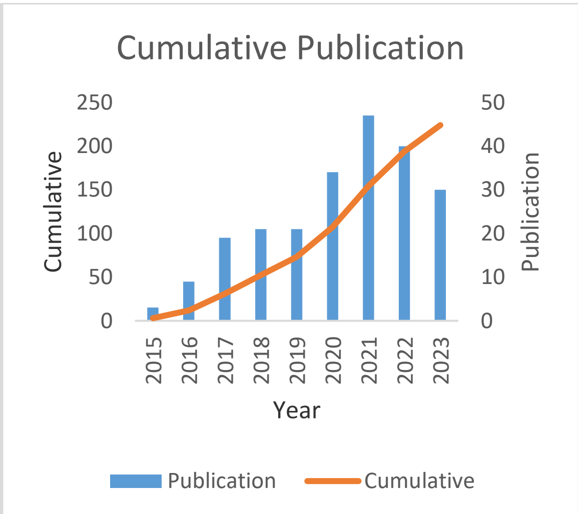


Figure. 3.7. Yearly document publications

Linear regression was performed to predict the number of publications up to 2030. Table III in appendix A shows the results of the linear regression model performed in excel. Linear regression is a statistical procedure for calculating the value of a dependent variable from an independent variable [33]. Linear regression predicts the relationship between two variables by assuming a linear connection between the independent and the dependent variables [34]. In this case the dependent variable is the number of publications, and the independent variable is the year of publication. To analyze this result, the null hypothesis was stated that ‘there is no relationship between the number of publication and the year of publication'. The alternative hypothesis was stated that 'there is a relationship between the number of publications and the year of publication'. The confidence level for this analysis was set to 95%. This meant that the α-value is 0.05. From table III in appendix A, the value of the significance F (also called the P-value) is 0.015513315 which is smaller than the α-value of 0.05. Thus the alternative hypothesis was upheld and the null hypothesis was rejected. Equation 3.1 is the simple linear regression model with X the independent variable i.e. the year of publication and Y the dependent variable or the predicted variable which in this case is the number of publication while m and b are the slope and y-intercept respectively of the graph. Equation 3.2 is the simple linear regression model with values of m and b as calculated in excel.

$$Y = mX + b \tag{3.1}$$

$$Y = 3.9667X - 7984.7 \tag{3.2}$$

In a simple linear regression, there is one independent variable and one dependent variable. The model estimates the slope and intercept of the line of best fit, which represents the relationship between the variables. For example, fig. 3.8 represents the linear relationship between the output(y) and predictor(x) variables. The blue line is called the best-fit straight line. The best fit line refers to a line through a scatter plot of data points that best expresses the relationship between these points [35]. According to [35] this line of best fit is used to show a trend or correlation between the dependent variable and independent variable(s). It can be depicted visually, or as a mathematical expression. In finance for instance, the line of best fit is used to identify trends or correlations in market returns between assets or over time [35]. Fig. 3.9 (a) is year fit line for predicted publication. [36] defines a normal probability plot as a plot comprising points that lie close to a line whose data comes from a distribution that is approximately normal. Fig. 3.9 (b) is the normal probability plot.

Table IV shows the predicted number of publications for the years 2024 through to 2030 using the linear regression model of (3.2). Here the Y-column indicates an increasing trend in the number of publications. This is an indication that there is growing interest in research on solar cell parameter extraction methods. The reason could be that the effects of climate change due to carbon dioxide emissions from fossil fueled power plants has aroused interest in researchers to find alternative ways of generating electricity such as the use of solar photovoltaic technology. Fig. 3.10 shows the graph of predicted cumulative publication up to 2030 based on linear regression model of (3.2). According to the model cumulative publication is expected to reach about 600 by year 2030. Fig. 3.11 shows document publication by country. From the figure it is observed that China, India and Egypt respectively published the highest number of documents on solar cell parameters extraction methods. In recent years, China has seen a sharp increase in the number of studies into Chinese solar PV technology, industry and policy, and these studies have uncovered some major factors that have contributed to the rapid rise of the Chinese PV industry [37].

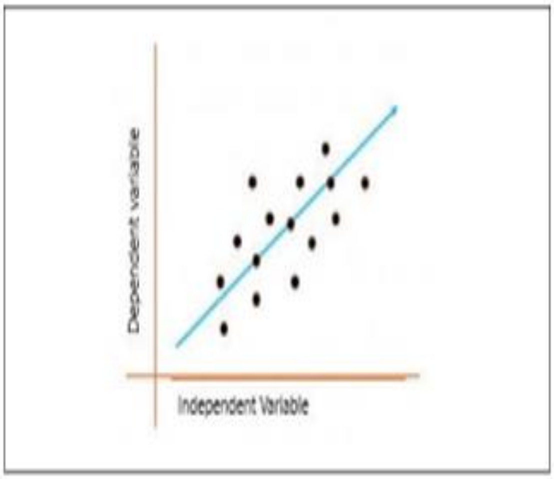


Figure. 3.9 (a) Best fit line

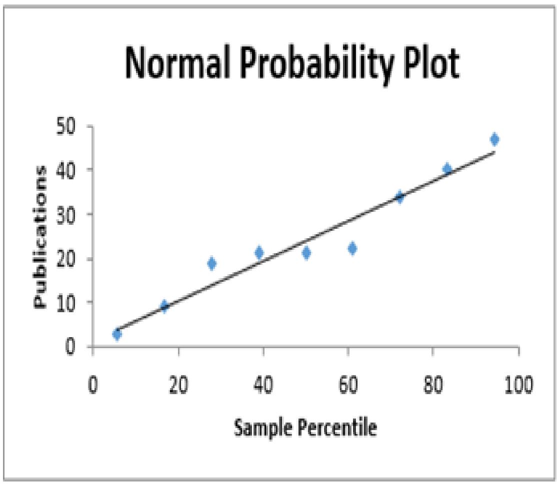


Figure. 3.9 (b). Normal probability output

Table IV. Predicted document publications

X (Year)	Y (Predicted publication)
2024	44
2025	48

2026	52
2027	56
2028	60
2029	64
2030	68

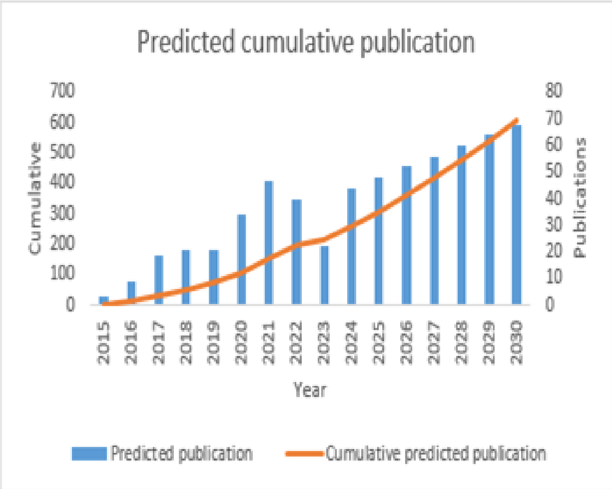


Figure. 3.10. Predicted cumulative publication

Figure. 3.11. Document publication by country

Fig. 3.12 shows the graph of total number of document citations each year from 2015 to 2023. From the figure it is easily seen that citations increased almost linearly from 2015 reaching a maximum of roughly 2500 citations in 2018. From 2018 the number of citations decreased reaching its lowest value of less than 500 in 2022. There were no citations recorded in 2023. Probably the reason 2023 did not receive any citation could be that documents published by 28th October 2023 had not yet been accessed by many researchers. Table V in appendix B shows statistics on country publications. Fig 3.13 is the graph of citation by country. Again China is seen as the leading country in document citations followed by Egypt and Iran. Though India is second to China in terms of document publication, it did not receive as many citations as Egypt and Iran. Equally Morocco and Saudi Arabia did not receive as many citations showing that citation does not have to depend on the number of publications.

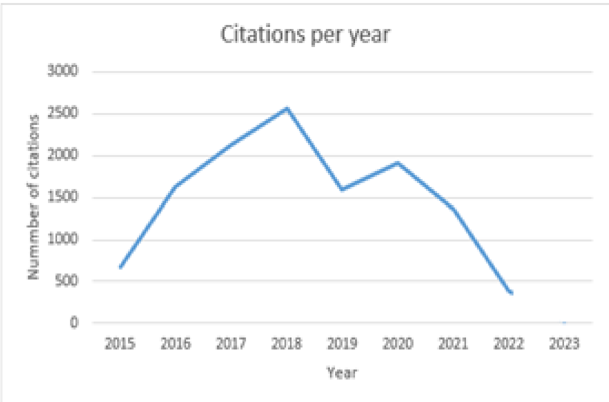


Figure. 3.12. Document citation per year

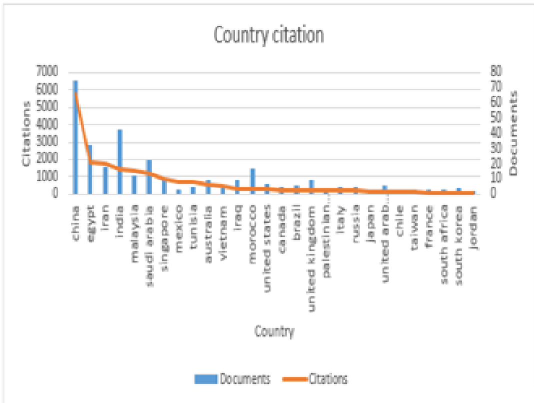


Figure. 3.13. Document citation by country

Co-authorship/Organization: In creating the networks for this analysis, the maximum number of organizations per document was set to 25 (default). The minimum number of documents per organization was set to 4. With these specifications, 31 organizations met the threshold out of a total of 316. And of the 31 organizations that met the threshold, 26 organizations formed the largest set of connected organizations. Fig. 3.14 is the network visualization map from VOSviewer. From the figure and going by the size of nodes, Wenzhou University, Zagazig University, Guizhou University, and University of Tehran collaborated most in research and document publications on solar cell parameters extraction methods. Fig. 3.15 is the density visualization map and shows organizations (in bright yellow colour) such as Wenzhou University, Zagazig University, Guizhou University, University of Tehran and Anna University, Chennai with high frequency in terms of collaboration with other organizations in document publications on solar cell parameter extraction methods. Fig. 3.16 is the overlay visualization map and shows organizations whose documents on solar cell parameters extraction methods had profound impact on publications made in 2021 and 2022. Organizations such as King Saudi University, Université Ibn Zohr (obscured in the map by Zagazig University) and Anna University, Chennai are prominent.

Fig. 3.17 is the graph of citation versus document publication. The figure shows that Jiangsu University has the highest number of citations despite having 7 publications. Other organizations with many citations but few publications include East China University of Science and Technology with 4 publications and 1024 citations and Zhengzhou University with 4 publications and 619 citations. Again this is an indication that citation does not have to depend on the number of publications. Table VI in appendix C shows statistics of document publication and citations by organization. Organizations are arranged according to the number of citations their documents received, with Jiangsu University topping the table with 1,239 citations. Fig. 3.18 shows citation impact of different organizations on document publication. It can be seen that organizations such as King Saud University despite having fewer citations, it has a higher normalized citation value compared to, say, Zagazig University with more citations but smaller value of normalized citation

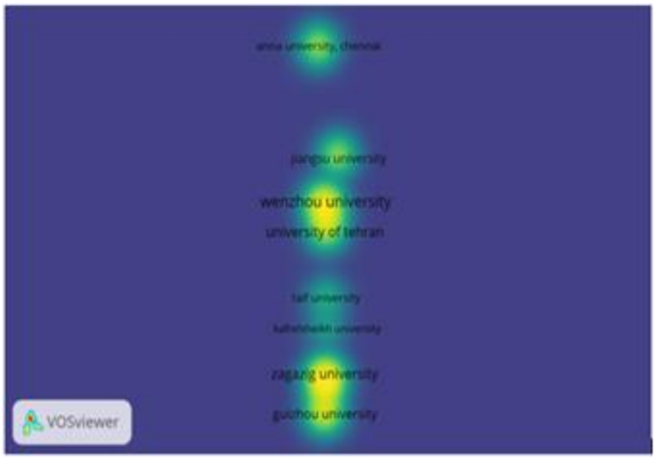


Figure. 3.14. Network visualization: co-authorship/ organization

Figure. 3.15. Density visualization map.

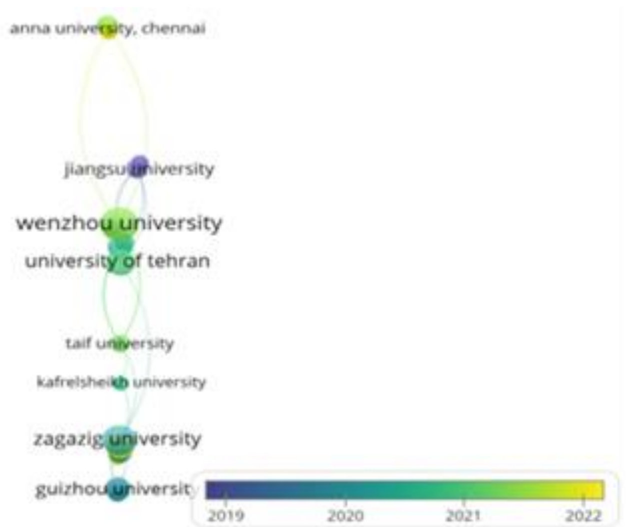
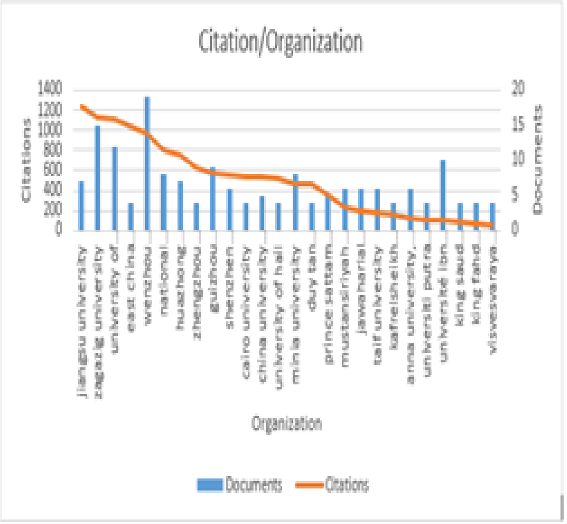


Figure. 3.16. Overlay visualization: co-authorship/organization



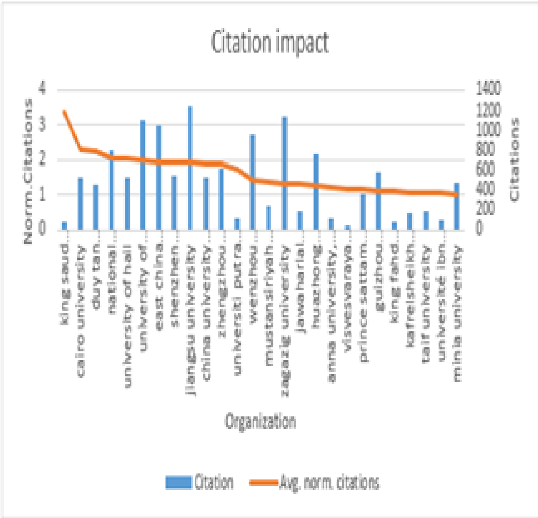
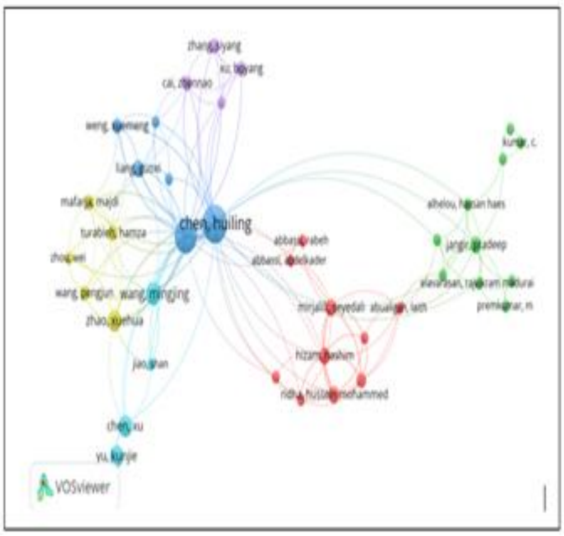


Figure. 3.17. Co-authorship/organization: citation and publication Figure. 3.18. Citation impact of organizations

Co-authorship/author: In creating network visualization map for this analysis, the maximum number of authors per document was set to 25 (default). The minimum number of documents per author was set to 2. With these settings, 134 authors met the threshold out of 663 authors. Of the 134 authors who met the threshold, 39 formed the largest set of connected authors. Fig. 3.19 is a screenshot of network visualization map from VOSviewer. Once again the size of the nodes indicates authors with large number of publications. In this case Chen Huiling and Heidari Ali asghar have the largest number of document publications. Fig. 3.20 is density visualization map. The bright yellow colour indicates frequency of occurrence. It can be observed that Chen Huiling, shown by the brightest yellow circle, has appeared more frequently in terms of collaborating with other authors in research and document publication on solar cell parameters extraction methods.



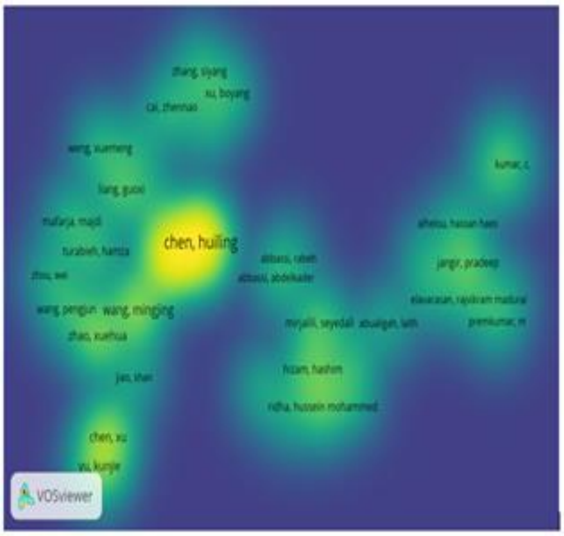


Figure. 3.19. Network visualization map: Co-authorship/author Figure. 3.20. Density visualization map: Co-authorship/author

Fig. 3.21 shows the overlay visualization map. The map indicates authors (bright yellow nodes) such as Zhang Siyang, Xu Boyang, Cai Zhennao, Kuang Fangjun, Weng Xuemeng, Zhon wei,Wang Pengjun, Premkumar Manoharan, Jangir Pradeep, Kumar Chandrasekaran, Abualigah Laith, Yaacob Mohammad Effendy, Hizam Hashim, Othman Mohammad Lutfi and Ahmadipour Masoud whose documents had produced high impact on documents published on solar cell parameters extraction methods particularly in the years 2021 and 2022. Table VII in appendix D shows statistics of document publication by author with largest set of connections. The authors are arranged in terms of the number of documents published. Generally, except for a few outliers, the number of publications corresponds to total length strength (TLS) i.e. authors with large number of publications also have large numbers of total length strength. Fig. 3.22 shows authors who have collaborated in publishing at least 4 documents on solar cell parameter extraction methods. From the figure, it is clear that Chen Huiling and Heidari Ali Asghar have the highest number of publications at 19 and 16 respectively.

Fig. 3.23 is the graph showing the relationship between the number of documents co-authored by given author(s) and the number of citations the documents received. Some authors such as Wang Mainigjing and Yu Hashim with few publications received a lot of citations. However, even if Chen Huiling and Heidari Ali Asghar have formed a strong relation in co-authoring of documents and have produced far more publications, the documents produced by Zhang Siyang, Xu Boyang, Cai Zhennao, Kuang Fangjun, Weng Xuemeng, Zhon Wei, Wang Pengjun, Premkumar Manoharan, Jangir Pradeep, Kumar Chandrasekaran, Abualigah Laith, Yaacob Mohammad Effendy, Hizam Hashim, Othman Mohammad Lutfi and Ahmadipour Masoud (shown as bright yellow dots in the overlay visualization of fig. 3.21) had produced more impact on document publication.

Fig. 3.24 shows author total length strength. Total length strength in this case refers to a strong relation between authors. Thus authors Chen Huiling and Heidari Ali Asghar have formed the strongest relation or connection in co-authoring of publications on solar cell parameters extraction methods. This is also illustrated as bright yellow circles in density visualization map of fig. 3.20.

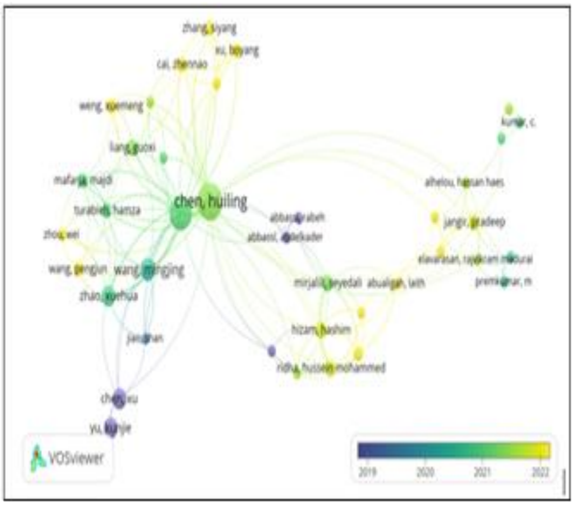


Figure. 3.21. Overlay visualization map: Co-authorship/author publications

Figure 3.22. Authors with at least 4

Figure 3.22. Authors with at least 4 publications and total link strength

Figure. 3.24. Author co-authored publication

Research question (RQ2) was answered using citation and co-citation analyses. The impact of publication is determined by the number of citations that it receives. Citation analysis is the study of the quantitative data derived from the use of citations as a means of determining the scholarly impact or influence and assumed quality of a journal, individual article, and an individual author or researcher [38]. [39] defines citation analysis as the examination of downstream citation frequency and pattern. Citation analysis enables the most influential publications in a research field to be ascertained [21]. Most highly cited scientific papers are defined as "research frontier" because the number of citations can be interpreted as sign of their importance as sources of new knowledge [26]. This network shows who has cited whom, and can be based on authors, documents, Journals, organizations or countries. Here the analysis is restricted to citation-authors, citation-documents and citation-journals.

According to [40], knowledge which is multidimensional, multifaceted, multidirectional and interdisciplinary in nature needs to be classified in order to understand its growth and evolution in a better way and so methods of knowledge classification have been developed over a period of time. One such method which has turned out to be the most effective method of knowledge mapping is co-citation analysis. Co-citation analysis is a variant of citation analysis and offers complementary insights into scholarly influence [41]. Co-citation analysis assumes publications that are cited together frequently and are thematically similar. In this bibliometric review, co-citation analysis was restricted to co-citation-cited authors and co-citation-cited sources.

Citation-author: In this analysis, the maximum number of authors per document was set to 25 (default). The minimum number of documents per author was set to 1. With these settings, 663 authors met the threshold. And of the 663 authors who met this threshold, 656 authors formed the largest network of connected authors. Fig. 3.25 is a screenshot of network visualization map from VOSviewer. The size of nodes corresponds to authors who have been highly cited. This is also shown by bright yellow circles in fig. 3.26 of the density visualization map which shows author frequency. Thus authors like Chen Huiling, Xiong Guojiang, Elyaqouti Mustapha, Gong Wenyin and Li Shuijia among others were highly cited. Fig 3.27 shows the first 20 highly cited authors. From the figure, authors Chen Xu, Heidari Ali Asghar and Yu Kunjie received the highest number of citations in excess of 1000. These authors can also be considered as being influential in the area of solar cell parameters extraction methods.

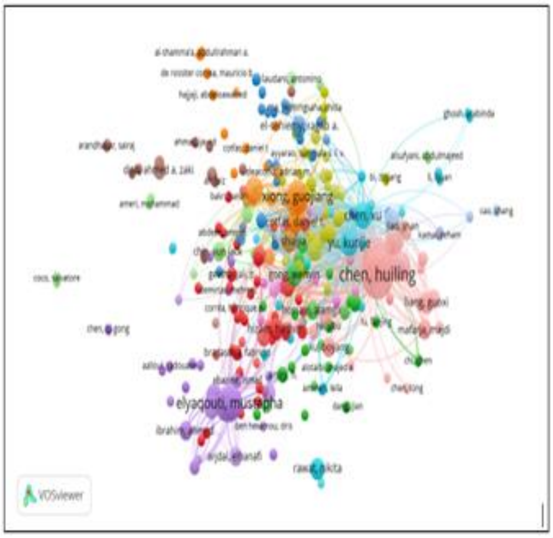


Figure. 3.25. Network visualization map: Citation/author

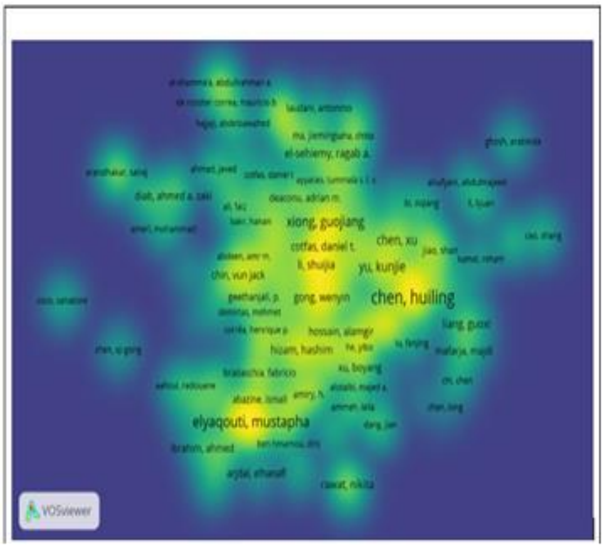


Figure. 3.26. Density visualization citation/author

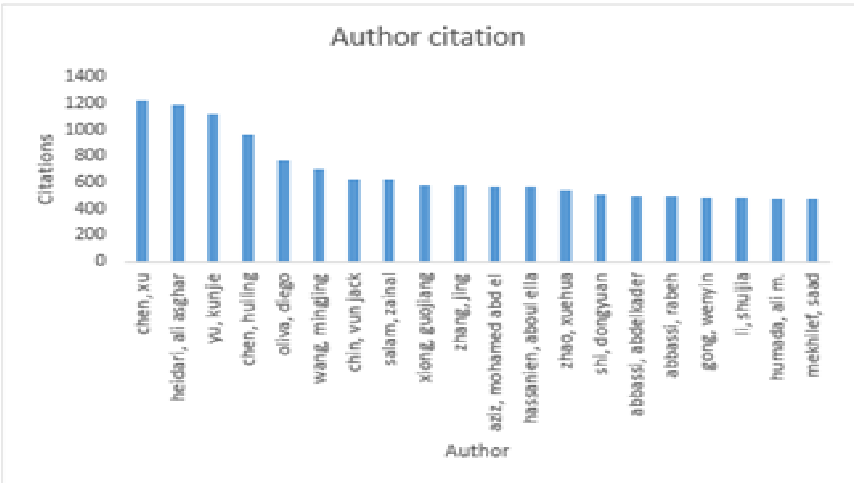
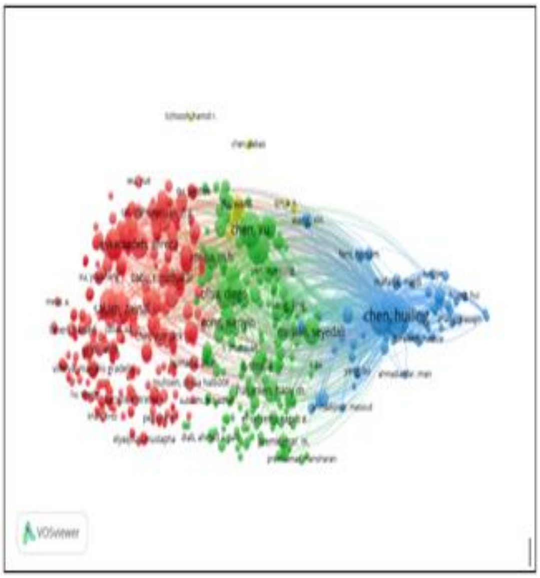


Figure. 3.27. First 20 highly cited Authors

Co-citation/cited authors: Here the minimum number of citations per author was set to 20 (default). With this setting 496 authors out of a total of 10928 met the threshold and equally formed the largest network of connected authors. Fig. 3.28 and 3.29 show the network and density visualizations maps for the co-cited authors. From fig. 3.25; 3.26; 3.28 and 3.29 authors such as Chen Huiling and Chen Xu have appeared very frequently as indicated by the sizes of the nodes. This shows that publications by these authors are among the highly influential and at the same time the impact of their publications is high. Fig. 3.30 shows the first 20 highly co-cited authors. In this analysis authors Chen Huiling, Heidari Ali Asghar, Chen Xu and Yu Kunjie have been co-cited in excess of 400 times. In citation analysis of fig. 3.27 the same authors are the highly cited researchers. So, it can be confidently said that these are the most influential authors in this field.

Fig. 3.31 and 3.32 show how author total length strength varies with citation basing on co-citation-cited author and citation-author analyses. It can be observed that authors like Chen Xu, Gong wenyin, Chen Zhicong, Chen Huiling, Zhao Xuehua and Yu Kunjie are among the 30 authors with high total length strength. Chen Xu, Chen Huiling and Yu Kunjie are also the highly cited authors in author citation analysis and co-citation-cited author analysis. Fig. 3.33a and 3.33b show how author document citation varies with author document publication and how author document publication varies with author document citation, respectively for the first 30 authors basing on citation/ author analysis. From the graphs of the two figures, it is clear that the number of citations don't necessarily depend on the number of publications. An author can have few publications but might receive many citations.



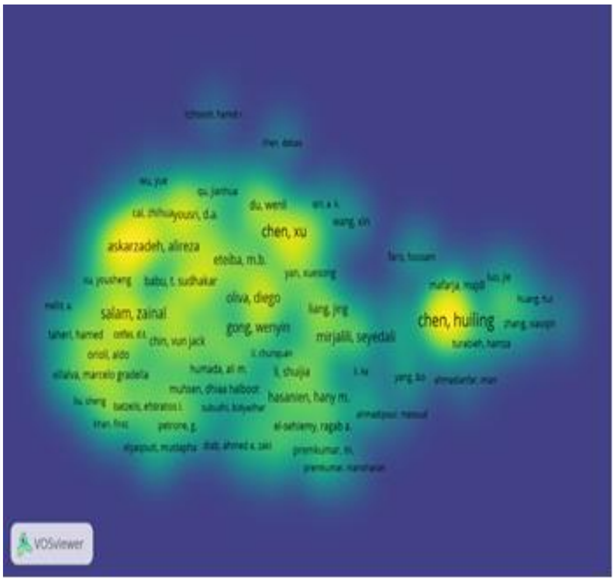


Figure. 3.28. Network visualization, co-citation-cited authors Figure. 3.29. Density visualization, co-citation-cited authors

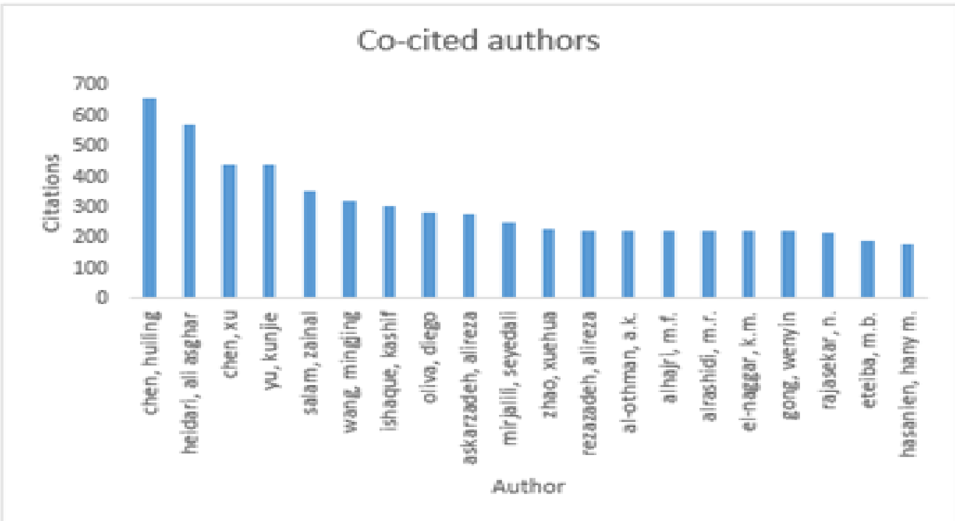
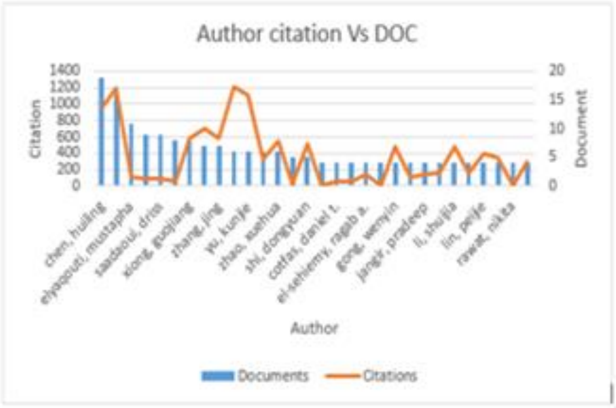


Figure. 3.30. First 20 highly co-cited authors

Figure. 3.31. Author total length strength based on on citation/author

Figure. 3.32. Author total length strength based co-citation/cited author



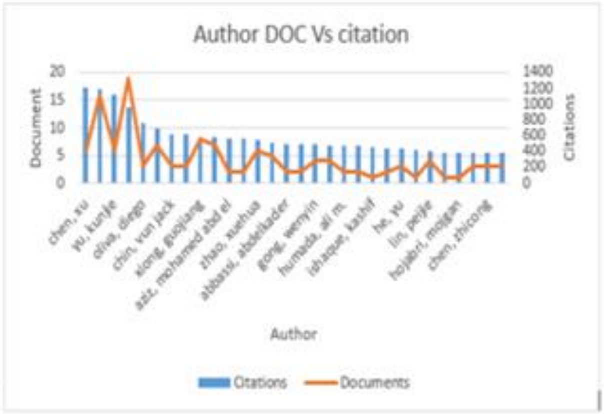


Figure. 3.33a. Variation of citation with Document

Figure. 3.33b. Variation of Document with citation

A chi-squared test statistic of independence /association was performed to test the hypotheses: number of citations an author receives is equal to the number of publications; number of citations an author receives is independent of number of publications. Table VIII and fig. 3.34 in appendix E show the results of chi-square test statistics performed in Statistics Kingdom [42]. The calculated p-value of 0.01591 is smaller than the alpha value of 0.05. This is indicated in fig. 3.34 in appendix E. With these results, the null hypothesis is rejected and it is concluded that the number of publications an author has is totally independent of the number of citations the documents receive.

Table IX shows authors with h-index in the period 2015 to 2023. Fig. 3.35 is the bar chart showing author h-index. The h-index is the number of publications at least having same number of citations [43] and this metric may be used to indicate influential authors in each research area. It is a number intended to represent both the productivity and the impact of a particular scholar or a group of scholars [44]. [45] define h-index as the measure of quantity with quality by comparing publications to citations and as such can be used for evaluating the cumulative impact of the author's scholarly output and performance. The metric corrects for the disproportionate weight of highly cited publications or publications that have not yet been cited. Going by this definition of h-index, then it can be said that the scholarly output by the authors Bayoumi Ahmed Saeed Abdelrazek, et al. and Naraharisetti Jaya Naga Lakshmi, et al., had high impact going by their h-index numbers.

Table IX. Authors h-index

S/N	Author	Times cited	h-index
1	Bayoumi, Ahmed Saeed Abdelrazek	24	23
2	Naraharisetti, Jaya Naga Lakshmi	23	23
3	Yeh, Weiâ€Chang	19	17
4	Abdulrazzaq, Ali Kareem	12	12
5	Choulli, Imade	4	4

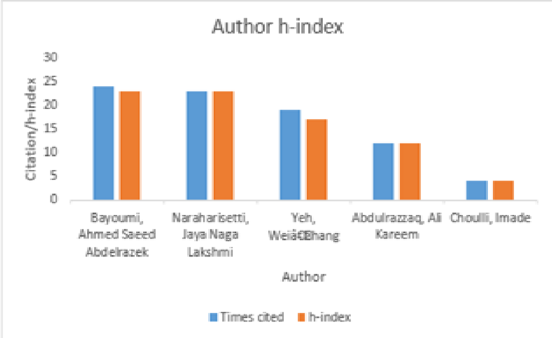


Figure. 3.35. Author h-index based on citation/author analysis

Citation/documents: In this analysis of citation / document, the minimum number of citations per document was set to 1. With this settings, 205 documents out of 224 met the threshold. Of the 205 documents which met the threshold, 201 formed the largest network of documents. Fig. 3.36; 3.37 and 3.38 are screenshots of network visualization, density visualization and overlay visualization maps from VOSviewer. From fig. 3.36 and 3.37, going by the size of the nodes, documents such as Oliva (2017a), Chi (2015), Jordehi (2016), Chen (2016b), Abbassi (2019), Humada (2016), Long (2020) and Abbassi (2018) received more citations in the period 2015 to 2023. The overlay visualization map of fig. 3.39 shows documents (yellow circles) with high impact factor on publication. Documents such as Long (2020), Wang (2021c), Batzelis (2022), Janani (2021), Abdellatif (2022), Weng (2022), Weng (2021) and Song (2022) among others have higher impact factor compared, say, to the document such as olive (2017a) and Chin (2015) despite these documents receiving a large number of citations.
The first 30 highly cited documents and year of publication are shown in fig. 3.39. From the figure the documents Ram (2017), Humada (2016) and Chen (2016a) received a lot of citations. Fig. 3.40 shows the number of document citations received in a given year. From this figure it is obvious that there were no citations made in the year 2023 though according to fig. 3.6, 30 documents were published by 28th October 2023. The largest number of citations were made in the year 2018 though only 21 documents were published in the year 2018 as shown in fig. 3.6 above. Probably the reason could be that a lot of researchers have shown interest in this subject, especially that there is a consensus to shift from depending on fossil fuels for power generation to renewable energy and in particular solar energy through the use of solar photovoltaic.

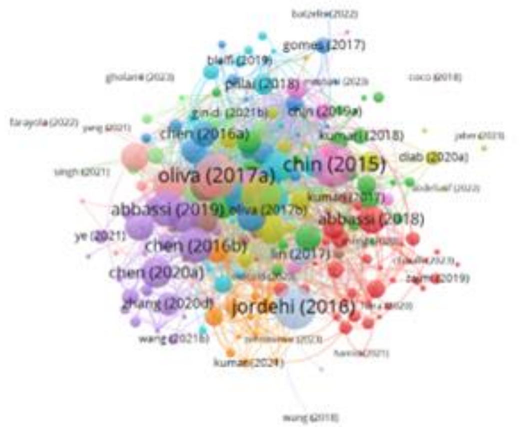


Figure. 3.36. Network visualization-document citation analysis

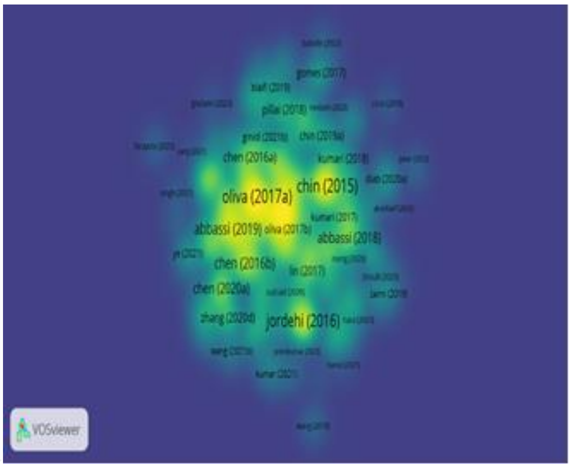


Figure. 3.37. Density visualization-document/citation

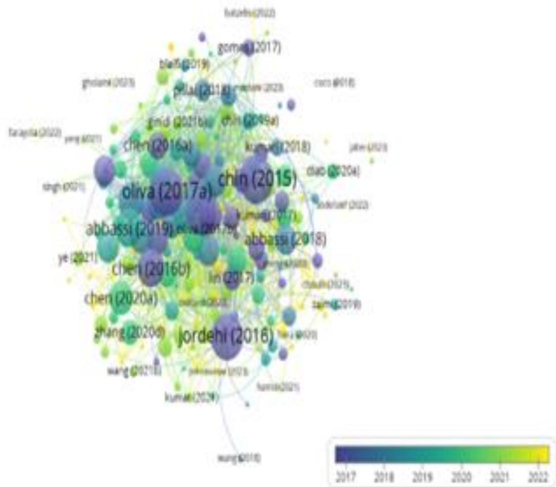


Figure. 3.38 Overlay visualization: document/citation

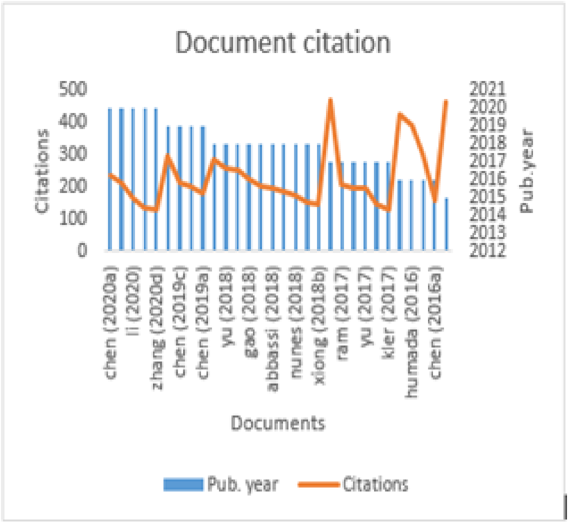


Figure. 3.39. First 30 highly cited documents

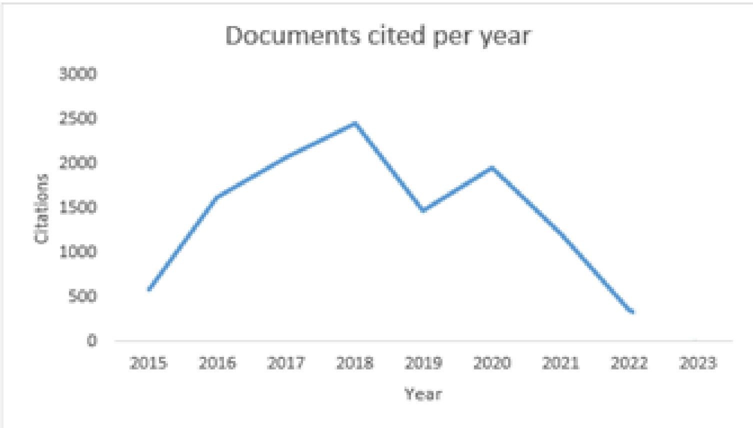


Figure. 3.40. Document citation in each year.

Table X in appendix F shows statistics on first 30 highly cited documents. It can be observed that some documents though may have high citations values have weak links. For example, documents Oliva (2017a), Jorden (2016) and Abbassi (2019) have high citation values but very weak links. A link here refers to citations between publications.

Citations/Journal: In this analysis the minimum number of documents and citations of a source were both set to 1. With these settings, 67 Journals out of 76 met the threshold. Of the 67 Journals which met the threshold, 64 constituted the largest number of connected Journals. Fig. 3.41; 3.42 and 3.43 are screenshots of the network visualization, density visualization and overlay visualization maps from VOSviewer. From fig. 3.41 and 3.42, going by the size of the nodes, the Journals Renewable energy, Solar energy, Energy conversion and management, Energy reports and IEEE Access have made a lot of publications on solar cell parameters extraction methods. Journals which have had high impact factor in the period 2015 to 2023 as can be seen from fig. 3.43 (bright yellow circles) are Applied Sciences, Energy Reports, Renewable and Sustainable Energy Reviews, Neural Computing and Applications, Eureka Physics and Engineering, IEEE Transactions on Sustainable computing, Engineering Research and Express, Material Today Proceedings and Optical Control and Applications. Fig. 3.44 and table XI in appendix G show the first 20 highly cited sources. Although the Journal of Energy Conversion and Management tops the list with 3,893 citations, it has also published 39 documents. However, the Journal of Renewable and Sustainable Reviews published only 9 documents but received 1,347 citations. Fig. 3.45 is the graph of normalized citations. From the graph, the Journal of Energy Conversion and Management has a higher value of normalized citation. Once again the Journal Energy Reports despite having few citations has a higher normalized citation value.

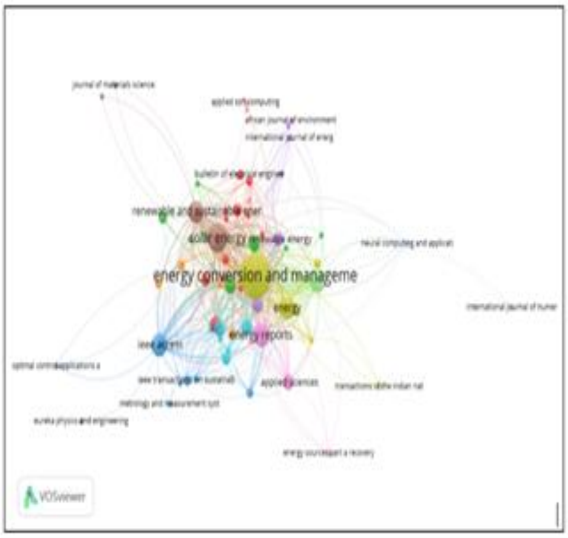


Figure. 3.41. Network visualization; citation/sources

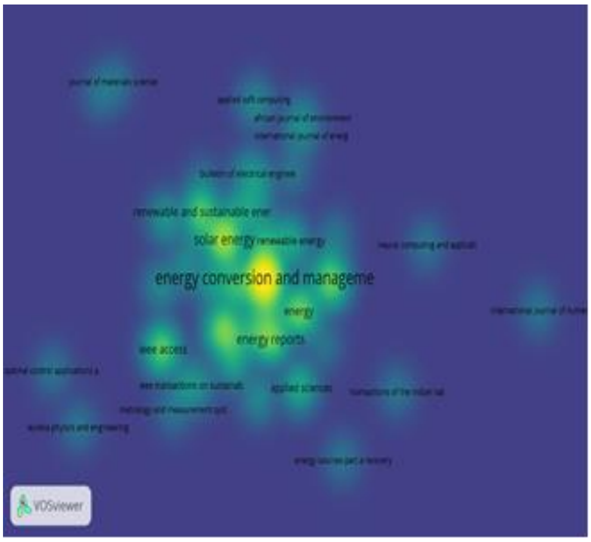


Figure. 3.42. Density visualization: Citation/sources

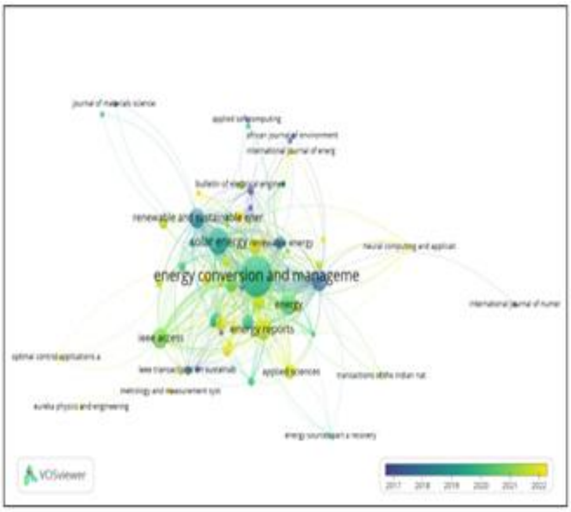


Figure. 3.43. Overlay visualization: citations/sources

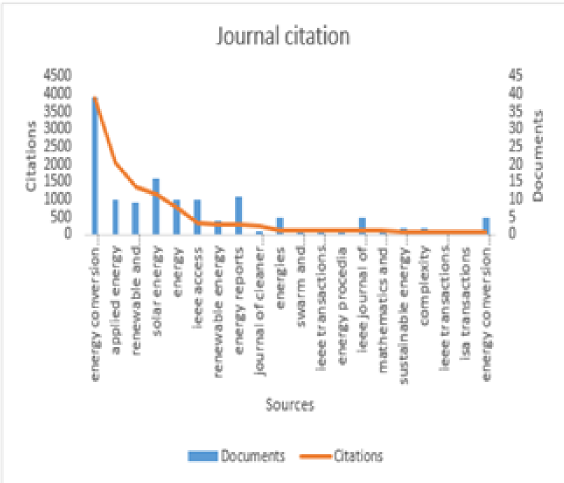


Figure. 3.44. First 20 highly cited sources: Citation/source

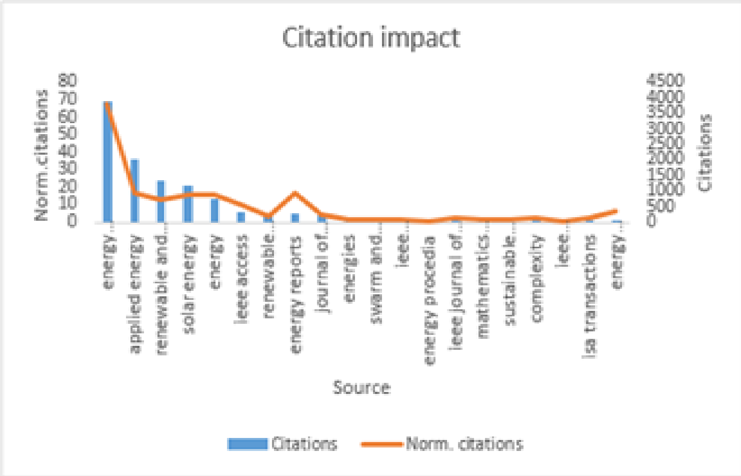
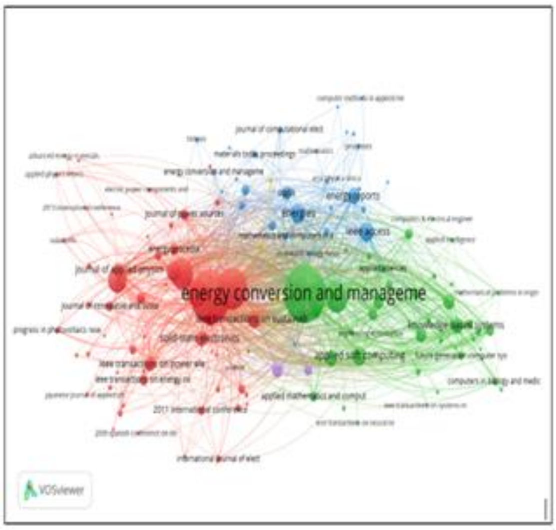


Figure. 3. 45. Journal citation impact

Table XI in appendix G shows some statistics on first 20 highly cited sources. It is clear that generally the number of documents and citations correspond to total length strength in most cases.

Co-citation/cited sources: Co-citation is the frequency with which two documents are cited together by other documents [46]. In this analysis the minimum number of citations of a source was set to 10. Of the 1,081 sources, 139 met the threshold. Fig. 3.46 and 3.47 are screenshots of network visualization and density visualization maps from VOSviewer. From fig. 3.46 and 3.47 the Journal of Energy Conversion and Management features prominently as the highly co-cited source. The same prominence of this Journal was observed in fig. 3.41 and 3.42 under citation/cited sources analysis. In fig. 3.48 the Journal of Energy Conversion and Management again shows high values of citations and total length strength. Other sources with notable numbers of citations and total length strength include the Journal of Solar Energy, Applied Energy, Renewable Energy, Energy and, Renewable and Sustainable Energy Resources. Fig. 3.49 shows the first 20 highly co-cited sources. Here the Journal Energy Conversion and Management and the Journal Solar Energy were highly co-cited with citations in excess of 1,000



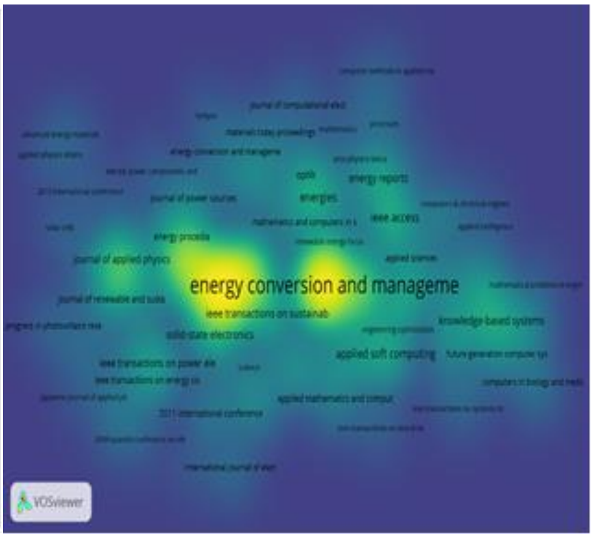
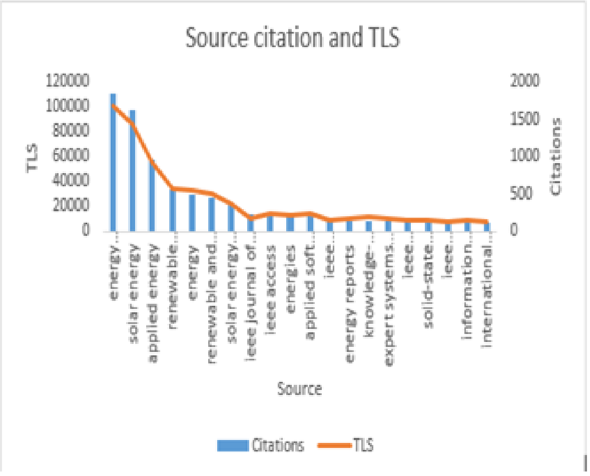


Figure. 3.46. Network visualization: Co-citation/cited sources

Figure. 3.47. Density visualization: Co-citation/cited sources



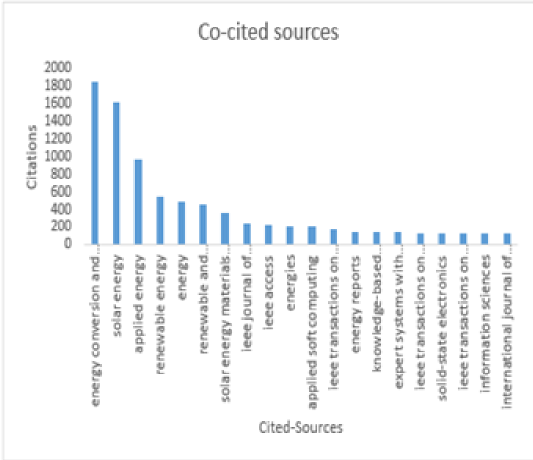


Figure. 3.48. Citations and total length strength of a source: Co-citation/cited sources

Figure. 3.49. First 20 highly co-cited sources

Co-occurrence of key words analysis: Research questions RQ3 and RQ5 were answered using co-occurrence network of key terms. Keywords shed light on which research topics in each field are popular or less popular [47] and have been widely used to reveal the knowledge structure of research domain [48]. Keyword analysis examines the actual content of the publication itself [21] and can therefore provide a preview of future research field. In creating the co-occurrence of terms network, the option of co-occurrence of terms based on text data was chosen. In analyzing this network, the minimum number of occurrence of a term was set to 10 (default). This means that each of these keywords has appeared in at least 10 documents. Of the 4,601 terms, 143 met the threshold. From this number of co-occurrence of key terms, 86 terms were selected. After removing non-key terms, 39 terms with at least 10 occurrences were included in creating a network of connected key terms. Fig. 3.50 and 3.51 are screenshots of network and density visualization maps from VOSviewer.

Fig. 3.52 is the overlay visualization map. In interpreting the visualization map, the lighter coloured nodes, yellow in this case, indicate keywords or topics of more recent interest [49]. Thus from fig. 3.52, keywords such as single diode model, double diode model, triple diode model, shunt resistance, photovoltaic cell etc. are some of the keywords which have formed topics of recent study. According to [50], the 2021 value shown in bright yellow in the colour bar indicates the point of increase of the used keyword number in Journal articles up to the present time. Also larger nodes such as that of extraction, diode model, photovoltaic module, single diode designate the topics that may be considered central during a given time frame i.e. the period 2015 to 2023 in this case. In further analyzing fig. 3.52, evolution of central research topics can be grouped into three periods according to the colour bar in the right-hand bottom corner of fig. 3.52. These are early adopters' period, middle period and the research front [49]. Early adopters shown in dark purple of fig. 3.52 were concerned with keywords such as solar cell model, generic algorithm and art algorithm. These were the focus of research up to mid-2019. The middle period indicated by dark green nodes included photovoltaic model and diode model which formed research areas up to mid-2020.

The keywords appearing as light green and yellow nodes form the research front [49]. These keywords include triple diode model, single diode model, double diode model, meta heuristics algorithm, shunt resistance, ideality factor, error etc. In fig. 3.52, keywords shown by small nodes (low frequency) such as parameter extraction methods, shunt resistance, metaheuristic algorithm, parameters identification, particle swarm optimization, generic algorithm, meta heuristic algorithm reflect the lack of these subjects in scientific papers in a given field [51], in this case the field of solar photovoltaic. Additionally, keywords represented by smaller spheres such as those appearing in fig. 3.52 means that these keywords are of low frequency and usually have one line or a few lines connecting them to other keywords. These keywords are in the boarder of research area [52] and might be connected through a keyword which is high in frequency. Table XII in appendix H shows the key words on solar cell parameters extraction methods arranged according to their occurrence in the network.

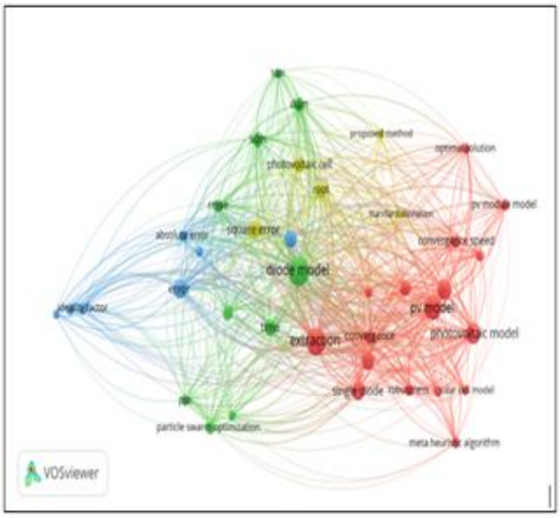


Figure. 3.50. Network visualization of co-occurrence of keywords

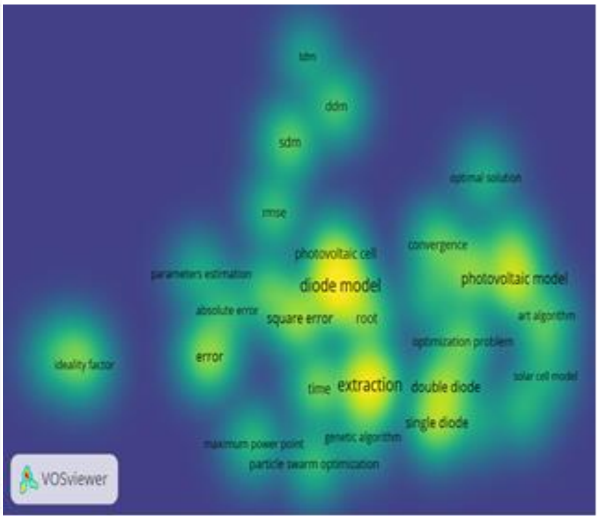


Figure. 3.51. Density visualization: Co-occurrence of key words

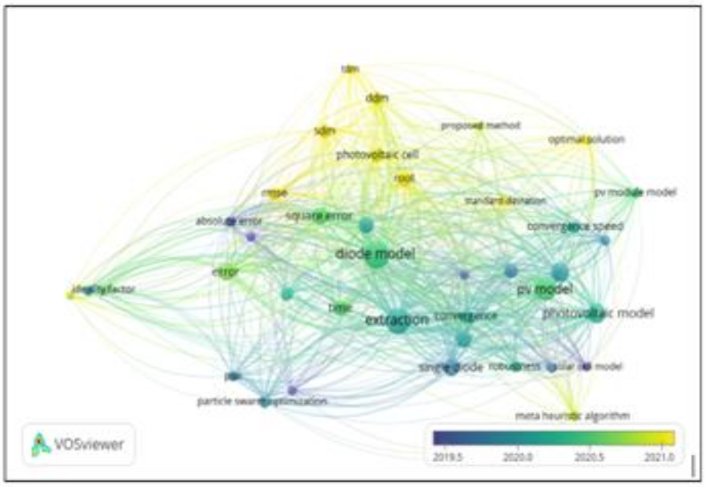


Figure. 3.52. Overlay visualization map

In fig. 3.53 the average citation of key words is shown. Keywords such as single diode model, and double diode model have small average citations values and at the same time have small occurrence values in the network. Similarly, keywords such as particle swarm optimization and ideality factor have small values of average citation and also small occurrence values in the network. The same keywords have small values of average normalized citation in fig. 3.54. These keywords could form subjects within the field of solar photovoltaic which have not been given much attention. Additionally, from fig. 3.55, it can be observed that the keywords single diode model, double diode model and triple diode model have small values of total length strength (TLS). In this case the strength of a link refers to the number of publications in which these three keywords occur together. These are some of the keywords which may constitute research topics needed to explore the subject of solar cell parameter extraction methods.

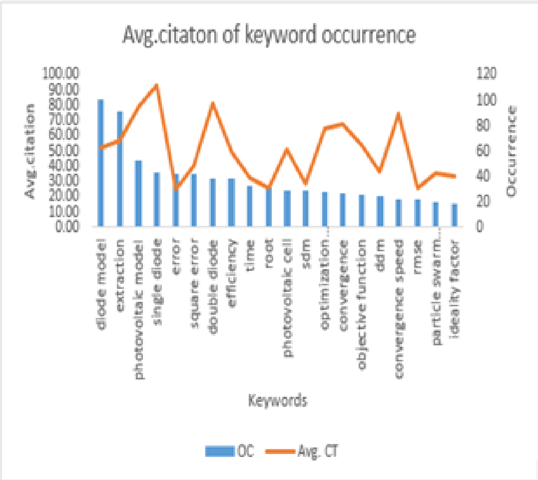


Figure. 3.53. Variation in average citations with keyword occurrence

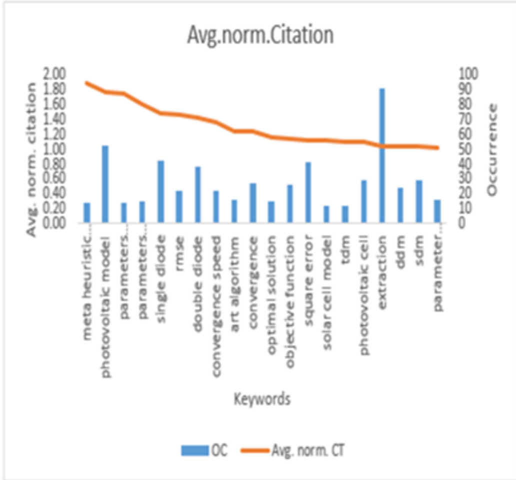


Figure. 3.54. Average normalized citation and occurrence of key words

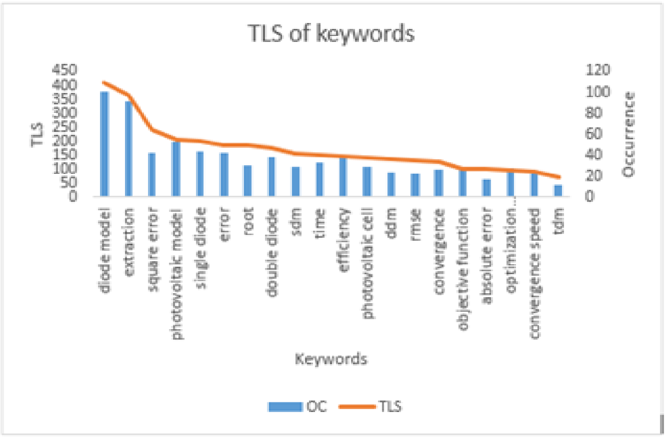


Figure. 3.55. Total length strength of key words

IV. Conclusion

Bibliometric analysis review of solar cell parameters extraction methods was conducted. Dimensions database was used to search for documents on this subject using key words “solar photovoltaic” OR “solar PV” AND “cell parameters” AND “extraction methods”. The search was limited to publications within the period from 2015 to 2023 and only documents of type ‘article’ were considered. Three hundred documents on this subject were retrieved. After screening the articles by title, 224 documents were included in the analysis. Five research questions were formulated to guide in bibliometric analysis. The technology of science mapping using VOSviewer was used to analyze the data. Analyses were done under the following categories (a) Co-authorship network. Under this network analyses and unit of analyses of Co-authorship and country, co-authorship and organization and co-authorship and author were used. Under co-authorship and country and co-authorship and organization research questions RQ1 and QR4 were answered.

The analysis revealed an increasing trend in publication from 2015 to 2023. Using Linear Regression Model, a further increase in publication on solar cell parameters extraction methods in future was predicted. Countries which collaborated most in research and publication in this field are China, India, Egypt, Malaysia, Morocco and Iran. China is leading with most publications followed by India. Leading organizations in document publication with at least 10 documents are Wenzhou University, Zagazig University, University of Tehran and Université ibn Zohr. Only two authors, Chen Huiling and Heidari Ali Asghar produced more than 10 documents. (b) Citation and co-citation networks. Under these networks, analyses and unit of analyses of citation/author, citation/document, citation/source, co-citation/cited authors and co-citation/cited sources were used. These citation networks were used to answer research question RQ2.

Under these analyses influential authors in this field were identified. These are authors who have been cited the most and have also done many publications. These are Chen Huiling, Xiong Guojiang, Elyaqouti Mustapha, Gong Wenyin and Li Shuijia. The chi-squared test statistic employed indicated that the number of publications does not necessarily correspond to the number of citations an author may receive in each period. (3) Co-occurrence network. Under this analysis data was analyzed in terms of occurrence of key words. This network was used to answer research questions RQ3 and RQ5. The co-occurrence of key words or terms was analyzed by interpreting the overlay visualization map. In this interpretation key words such as single diode model, double diode model, triple diode model, shunt resistance form topics which are of recent study. Further, the appearance of these key words, including keywords such as ideality factor, metaheuristic algorithm, particle swarm optimization forms the research front.

Basing on this review, it is recommended that more study on solar cell parameters extraction methods be conducted in regions which are underrepresented, such as the Sub-Saharan Africa and Latin America where no or very few studies of this nature have been done. Investigations on solar cell parameters extraction methods should not only be restricted to underrepresented regions but should be an on-going activity so that current methods can be improved on, and new methods discovered. It is also recommended that investigation on keywords that form the research front be conducted to further investigate the effect of these parameters on solar cell performance.

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Appendix A

Table III Linear regression results

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.768622236
R Square	0.590780142
Adjusted R Square	0.532320162
Standard Error	9.665352948
Observations	9

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	944.0667	944.06667	10.10571924	0.015513315
Residual	7	653.9333	93.419048		
Total	8	1598			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-7984.7	2519.294	-3.16942	0.015720539	-13941.88251	-2027.51749	-13941.9	-2027.52
Year	3.966666667	1.247792	3.1789494	0.015513315	1.016108152	6.917225182	1.016108	6.917225

RESIDUAL OUTPUT

Observation	*Predicted Publications*	*Residuals*	*Standard Residuals*
1	8.133333333	-5.13333	-0.567777
2	12.1	-3.1	-0.342878
3	16.06666667	2.933333	0.3244439
4	20.03333333	0.966667	0.106919
5	24	-3	-0.331818
6	27.96666667	6.033333	0.6673222
7	31.93333333	15.06667	1.6664621
8	35.9	4.1	0.4534842
9	39.86666667	-17.8667	-1.976159

PROBABILITY OUTPUT

Percentile	*Publications*
5.555555556	3
16.66666667	9
27.77777778	19
38.88888889	21
50	21
61.11111111	22
72.22222222	34
83.33333333	40
94.44444444	47

Appendix B

Table V. Statistics on country publications

DOC = Document; %DOC = Percentage Document; Avg. CT = Average Citation; TLS = Total Link Strength

Rank	Country	DOC	% DOC	Citations	Avg. CT	TLS
1	China	75	33.48	5804	77.39	62
2	India	43	19.20	1453	33.79	24
3	Egypt	32	14.29	1812	56.63	40
4	Saudi Arabia	22	9.82	1151	52.32	40
5	Iran	18	8.04	1780	98.89	30
6	Morocco	17	7.59	289	17.00	7
7	Malaysia	12	5.36	1341	111.75	23

8	Singapore	10	4.46	888	88.80	26
9	Australia	9	4.02	529	58.78	23
10	Iraq	9	4.02	331	36.78	21
11	United Kingdom	9	4.02	230	25.56	8
12	United States	7	3.13	257	36.71	10
13	Brazil	6	2.68	249	41.50	3
14	United Arab Emirates	6	2.68	156	26.00	14
15	Canada	5	2.23	256	51.20	5
16	Italy	5	2.23	185	37.00	6
17	Russia	5	2.23	177	35.40	12
18	Tunisia	5	2.23	672	134.40	6
19	Palestinian Territory	4	1.79	212	53.00	10
20	South Korea	4	1.79	62	15.50	10
21	Vietnam	4	1.79	459	114.75	11
22	France	3	1.34	94	31.33	2
23	Japan	3	1.34	165	55.00	6
24	Mexico	3	1.34	679	226.33	3
25	South Africa	3	1.34	66	22.00	7
26	Taiwan	3	1.34	151	50.33	5
27	Chile	2	0.89	153	76.50	4
28	Jordan	2	0.89	25	12.50	6

Appendix C

Table VI. Statistics of document publication and citation by organization

DOC = Document; %DOC = Percentage of Documents; CT = Citations; Avg. CT = Average Citation; TLS = Total Length Strength

Rank	Organization	CT	DOC	%DOC	Avg. CT	TLS
1	Jiangsu University	1239	7	3.24	177.00	9
2	Zagazig University	1137	15	6.94	75.80	14
3	University of Tehran	1105	12	5.56	92.08	28
4	East China University of Science and Technology	1042	4	1.85	260.50	4
5	Wenzhou University	962	19	8.80	50.63	38
6	National university of Singapore	806	8	3.70	100.75	25
7	Huazhong University of Science and Technology	757	7	3.24	108.14	8
8	Zhengzhou University	619	4	1.85	154.75	3
9	Guizhou University	581	9	4.17	64.56	7
10	Shenzhen Institute of Information Technology	546	6	2.78	91.00	17
11	Cairo University	531	4	1.85	132.75	3
12	China University of Geosciences	529	5	2.31	105.80	1
13	University of Hail	520	4	1.85	130.00	4
14	Minia University	472	8	3.70	59.00	11
15	Duy Tan University	459	4	1.85	114.75	12
16	Prince Sattam Bin Abdulaziz University	357	5	2.31	71.40	8

17	Mustansiriyah University	236	6	2.78	39.33	7
18	Jawaharlal Nehru Technological University, Kakinada	195	6	2.78	32.50	1
19	Taif University	182	6	2.78	30.33	9
20	Kafrelsheikh University	160	4	1.85	40.00	2
21	Anna University, Chennai	119	6	2.78	19.83	6
22	Universiti Putra Malaysia	106	4	1.85	26.50	7
23	Université Ibn Zohr	103	10	4.63	10.30	4
24	King Saud University	87	4	1.85	21.75	4
25	King Fahd University of petroleum and minerals	75	4	1.85	18.75	5
26	Visvesvaraya Technological University	45	4	1.85	11.25	5

Appendix D

Table VII. Statistics of document publication by author: Co-authorship/author analysis

DOC = Document; %DOC = Percentage Document; CT = Citations; Avg. CT = Average Citations; TLS = Total Link Strength

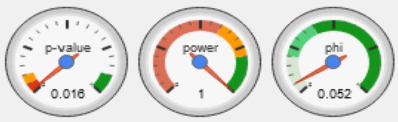
Rank	Author	DOC	%DOC	CT	Avg. CT	TLS
1	chen, huiling	19	8.80	962	50.63	73
2	heidari, ali asghar	16	7.41	1190	74.38	64
3	wang, mingjing	7	3.24	700	100.00	22
4	chen, xu	6	2.78	1220	203.33	9
5	yu, kunjie	6	2.78	1117	186.17	4
6	zhao, xuehua	6	2.78	546	91.00	24
7	hizam, hashim	4	1.85	106	26.50	18
8	jangir, pradeep	4	1.85	149	37.25	13
9	liang, guoxi	4	1.85	159	39.75	17
10	mirjalili, seyedali	4	1.85	349	87.25	16
11	ridha, hussein mohammed	4	1.85	106	26.50	18
12	cai, zhennao	3	1.39	25	8.33	15
13	mafarja, majdi	3	1.39	83	27.67	15
14	othman, mohammad lutfi	3	1.39	49	16.33	13
15	turabieh, hamza	3	1.39	83	27.67	15
16	wang, pengjun	3	1.39	58	19.33	12
17	weng, xuemeng	3	1.39	33	11.00	12
18	xu, boyang	3	1.39	24	8.00	13
19	zhang, siyang	3	1.39	24	8.00	13
20	abbassi, abdelkader	2	0.93	495	247.50	4
21	abbassi, rabeh	2	0.93	495	247.50	4
22	abualigah, laith	2	0.93	25	12.50	8
23	ahmadipour, masoud	2	0.93	79	39.50	9
24	alhelou, hassan haes	2	0.93	68	34.00	7
25	elavarasan, rajvikram madurai	2	0.93	94	47.00	8
26	jiao, shan	2	0.93	448	224.00	9
27	kuang, fangjun	2	0.93	23	11.50	10
28	kumar, c.	2	0.93	44	22.00	2

29	kumar, chandrasekaran	2	0.93	19	9.50	8
30	liu, yun	2	0.93	76	38.00	9
31	muhsen, dhiaa halboot	2	0.93	186	93.00	5
32	premkumar, m	2	0.93	90	45.00	4
33	premkumar, m.	2	0.93	74	37.00	4
34	premkumar, manoharan	2	0.93	19	9.50	8
35	sowmya, r	2	0.93	90	45.00	4
36	xavier, felix joseph	2	0.93	26	13.00	2
37	ya'acob, mohammad effendy	2	0.93	27	13.50	9
38	ye, xiaojia	2	0.93	126	63.00	7
39	zhou, wei	2	0.93	28	14.00	9

Appendix E

Table VIII. Results of Chi-square test statistics [42]

k	2 x 30 = 60	Number of categories
n	17737	Sample size
χ^2	47.66755426262372	Chi square test statistic
DF	29	(Rows-1)*(Columns-1) = (30-1)*(2-1) = 29
Phi effect (Φ)	0.0518408	$\Phi=\sqrt{(\chi^2/n)}$
DF_{min}	1	Min(Rows-1,Columns-1) = Min(30-1,2-1) = 1
Cramer's V effect	0.0518408	$V = \Phi/\sqrt{DF_{min}}$



Independence (Association), using χ^2 distribution (DF=29) (right-tailed) (validation)

1. H_0 hypothesis

Since p-value < α, H_0 is rejected.

The statistical model does not fit the observations

A significant association was found between variable A and variable B

2. P-value

The p-value equals **0.01591**, ($p(x\leq\chi^2) = 0.9841$). It means that the chance of type I error (rejecting a correct H_0) is small: 0.01591 (1.59%).

The smaller the p-value the more it supports H_1.

3. The statistics

The test statistic χ^2 equals **47.6676**, which is not in the 95% region of acceptance: [-∞ : 42.557].

4. Effect size

The observed effect size phi is **small**, **0.052**. Cramer's V effect size is **0.052**. This indicates that the magnitude of the difference between the observed data and the expected data is small.

Figure. 3.34. Result of Chi-square test statistic of independence [42]

Appendix F

Table X. Statistics on first 30 highly cited documents

Rank	Document	Citations	Avg.Citations	Norm. citations	Links
1	oliva (2017a)	472	2.11	4.2005	9
2	chin (2015)	467	2.08	2.0942	29
3	jordehi (2016)	426	1.90	2.3507	3
4	humada (2016)	395	1.76	2.1796	11
5	chen (2016b)	301	1.34	1.6609	27
6	abbassi (2019)	300	1.34	3.9673	6
7	chen (2018)	286	1.28	2.3461	65
8	yu (2018)	258	1.15	2.1164	8
9	xiong (2018a)	252	1.13	2.0672	30
10	chen (2020a)	235	1.05	4.1876	11
11	gao (2018)	223	1.00	1.8293	66
12	chen (2019c)	213	0.95	2.8168	21
13	long (2020)	212	0.95	3.7778	10
14	ram (2017)	207	0.92	1.8422	23
15	elaziz (2018)	204	0.91	1.6734	21
16	li (2019)	200	0.89	2.6448	23
17	xu (2017)	197	0.88	1.7532	18
18	yu (2017)	197	0.88	1.7532	8
19	abbassi (2018)	195	0.87	1.5996	23
20	beigi (2018)	183	0.82	1.5012	18
21	chen (2019a)	180	0.80	2.3804	32
22	nunes (2018)	175	0.78	1.4355	22
23	li (2020)	165	0.74	2.9403	19
24	chen (2016a)	157	0.70	0.8663	26
25	merchaoui (2018)	152	0.68	1.2469	36
26	xiong (2018b)	149	0.67	1.2223	26
27	fathy (2017)	148	0.66	1.3171	14
28	liang (2020)	138	0.62	2.4591	24
29	zhang (2020d)	132	0.59	2.3522	19
30	kler (2017)	130	0.58	1.1569	14

Appendix G

Table XI. Statistics on first 20 highly cited sources

DOC = Document; % DOC = Percentage Document; Avg.CT = Average citation; Norm. CT =Normalized Citation; TLS = Total Length Strength

Journals	**DOC**	**%DOC**	**Citations**	**Avg. CT**	**Norm. CT**	**TLS**
energy conversion and management	39	17.41	3893	99.82	67.78	830
applied energy	10	4.46	2050	205	16.23	412
renewable and sustainable energy reviews	9	4.02	1347	149.67	12.93	282
solar energy	16	7.14	1172	73.25	15.50	304
energy	10	4.46	756	75.6	15.46	271
ieee access	10	4.46	333	33.3	9.50	204
renewable energy	4	1.79	293	73.25	2.90	80
energy reports	11	4.91	285	25.91	16.35	193
journal of cleaner production	1	0.45	235	235	4.19	42
energies	5	2.23	134	26.8	1.83	80
swarm and evolutionary computation	1	0.45	130	130	1.16	36
ieee transactions on sustainable energy	2	0.89	121	60.5	1.33	27
energy procedia	2	0.89	114	57	0.69	34
ieee journal of photovoltaics	5	2.23	113	22.6	2.16	23
mathematics and computers in simulation	1	0.45	113	113	1.01	21
sustainable energy technologies and assessments	2	0.89	89	44.5	1.59	35
complexity	2	0.89	88	44	2.27	47
ieee transactions on industrial electronics	1	0.45	78	78	0.43	14
isa transactions	1	0.45	78	78	2.70	21

Appendix H

Table XII. Statistics of key word occurrence

Rank	**Keyword**	**Occurrences**	**Avg. citations**	**TLS**
1	diode model	101	51.86	476
2	extraction	91	57.02	437
3	pv model	71	56.01	354
4	photovoltaic model	53	79.51	273
5	experimental result	49	74.49	245
6	single diode	43	92.91	245
7	error	42	24.93	209
8	square error	42	40.71	249
9	double diode	38	80.95	215
10	photovoltaic module	35	71.49	166
11	time	33	32.97	165
12	root	31	25.71	201
13	photovoltaic cell	29	51.14	155
14	sdm	29	28.69	181

15	optimization problem	28	65.21	121
16	convergence	27	67.59	156
17	objective function	26	54.00	118
18	ddm	24	36.25	159
19	convergence speed	22	74.95	122
20	rmse	22	25.95	145
21	particle swarm optimization	20	36.00	90
22	ideality factor	19	33.63	80
23	robustness	19	69.11	98
24	absolute error	17	56.94	107
25	pso	17	25.76	84
26	pv module model	17	54.47	86
27	series resistance	17	39.88	63
28	art algorithm	16	84.06	87
29	parameter extraction method	16	73.81	92
30	optimal solution	15	63.40	82
31	parameters identification	15	117.53	77
32	genetic algorithm	14	50.79	65
33	meta heuristic algorithm	14	73.50	66
34	parameters estimation	14	153.86	59
35	shunt resistance	12	40.33	49
36	solar cell model	12	115.67	54
37	tdm	12	32.67	87
38	standard deviation	11	29.91	65
39	proposed method	10	37.60	49