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REVIEW ARTICLE

A Bibliometric Analysis on Optimization Solution Methods Applied to Supply Chain of Solar Energy

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Abstract
This study shows a review and brief analysis of the most concepts and models in the supply chain of solar energy. The presented work of this study possesses two parts. In the first section, a brief introduction on supply chain of solar energy is addressed and then, in the second part, a detailed bibliometric analysis is performed on supply chain of solar energy. The bibliometric analysis has been performed as an influential tool for using in scientometrics and reviews, which for this aim, keywords and subject areas are discussed, and a review of problems and solution methods are provided as well. The results show that in terms of the subject area, energy fuels, green sustainable science technology, environmental sciences, environmental engineering, and chemical engineering are the most discussed areas amongst scholars. Also, based on findings, the majority of studies are deterministic approaches, while there is an urgent need to provide robust approaches for tackling uncertain situations. In the end, the conclusion and discussion are provided as the final section of this study.

Keywords Supply chain · Solar energy · Renewable energy · Optimization

1 Introduction

Suppliers, manufacturers, warehouses, distributors, and vendors are important factors of the supply chain that aim to develop the product, procurement of material, shipment of products, manufacturing products, and then distribute finished goods between plants [1, 2]. The roles of the supply chain are developing a new product, marketing, operating, warehousing, financing, and servicing customers [3]. Supply chain has been defined as a flow of product, money, and information that causes to dynamic inherent of the supply chain. The above-mentioned flow is between several stages of the supply chain namely, supplier, manufacturer, distribution centers, retailers, and customers [4–6].

Zarandi et al. [7] have worked different features of the supply chain that contains material movement, flow of information, and buyer to seller relations. The main goal of supply chain management is maximizing profit or minimizing cost [2, 3]. Decisions related to flow of information, product, and funds fall the main categories of the supply chain namely, strategic, tactical, and operational decisions [8, 9].

One of the most significant policy decisions in supply chain is related to facility location and technology selection. The main decisions related to tactical and operational phases such as warehousing and inventory are discussed once supply chain framework is identified [8, 10, 11]. Researchers mostly focus on production, inventory, location, transportation, and information that are known as the 5 top topics in supply chain and are related to facility location decisions. Some of the above-mentioned decisions can be optimized under different circumstance, but some others such as facility location decision problem are hard to change as they are called strategic decision [8, 9, 12].

As it is stated, facility location decision problem is carried out as strategically, which involves supply chain management. The above-mentioned decision provides decisions related to locating facilities namely, manufacturing, warehouses, storage of each facility, and other decisions related to supply chain network design. The decisions could be classified as follows [1, 3, 8, 9, 12]:

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- Facility location decision: decisions in relation to the location of facility, identify the open and closed facility.
- Capacity allocation decision: decision in relation to assigned capacity to each plant, or market and supply allocation, also discussing what customer each site should cover and which facility should be served by which source.

The important factors that have most contributions to network design of supply chain include strategic, technological, macroeconomic, and operational factors [3, 8, 13].

Decision-makers use network design in several circumstances. In the first place, these models discuss the potential location for sites and their capacities [8, 13].

In the second place, assigning demand to the facilities and their quantities for transportation is also applied.

Decision makers mostly use different scenario for analyzing, making decisions, and supply chain modeling [14]. The decisions should tackle the problems that arise from using different transportation modes, closing or opening new facilities, facility capacity, and the performance of supply chain. The aforementioned problems could be solved by modeling of logistics network and trying to test several scenarios on it and find the best solutions in each scenario.

The global economy is developing rapidly and consequently, energy requirements have been focused, particularly in developing countries. Due to climate change and environmental protection, fossil fuel resources are replacing by renewable energies [15].

The renewable energy concept has been applied to several sectors. Renewable energy is an energy, which is provided from renewable resources namely, sun, wind, marine, tides, waves, and geothermal energy [16]. Nowadays, many countries across the world already have renewable energy contributing to the energy supply and national renewable energy markets are predicted to continue to develop powerfully [17]. Solar energy is the second most usable and largest renewable energy [18].

Solar energy generation could be used to generate hot water via solar systems or electricity via solar photovoltaic (PV) and concentrating solar power systems. The above-mentioned technologies are technically well confirmed with several systems installed across the world over the last few decades [16, 19]: a PV system directly convert solar energy into electricity [20]; a CSP technology produces electricity by concentrating direct-beam solar irradiance and is used in a downstream process to produce electricity [16]. Solar thermal heating and cooling is another application of solar energy that provides thermal energy from the sun and is used in commercial and industrial applications [21].

Also, solar energy has been identified as a confidential source of renewable energy in some of the middle east countries [22–24]. So far, many researchers have studied hybrid renewable energy systems [25–28]. Fossil fuels are strongly finite and give a way to undesirable climate changes, while solar energy is deemed as one of the cleanest types of energy that can be used as a substitute to fossil fuels and can slow down global warming.

As for solar energy, solar panels are weather-dependent, which means they are dependent on sunlight to effectively gather solar energy. Therefore, a few cloudy and rainy days can have a noticeable effect on the energy system. Therefore, an appropriate optimization method is required to ensure having optimal number and size of PVs. Furthermore, combination of PVs and some other renewable energies in a hybrid energy system reduces the battery bank and diesel requirements [29–31]. In terms of objective function, variety of objective functions could be considered such as: gross profit of supply chain [32], profit of forward and reverse logistic [33], environmental impact [34], and total cost [35–37].

This paper presents a comprehensive review of optimization solution methods applied to supply chain of solar energy. Section 2 shows research methodology. Section 3 provides research question and Sect. 4 presents bibliometric analysis. Optimization solution methods and statistical analysis on solution approaches have been illustrated in Sect. 5 and 6, respectively. Conclusion and directions for future study have been provided in the last section.

2 Research Methodology

The research procedure in this paper has been divided in five stages. In the first stage, documents from databases are gathered. Scopus and WOS are two main databases for our goal that have been used. Before start searching in databases, some special keywords namely, "solar energy" and "supply chain" have been selected to filter the search. Moreover, it is worthy to note that type of found documents includes only research articles excluding book, book, chapter, review, conference paper, and short letter leading to finding 305 published articles from WOS and Scopus, as of writing this paper. Many of found articles are duplicates so it is necessary, in stage 2, to identify and remove them from our library; to achieve this aim, Mendeley as powerful reference manager is used. Also, in stage 2 some research questions for this study are designed. In stage 3, social network analysis has been used to provide a bibliometric analysis for documents. For this aim, VOSviewer and CitNetExplorer have been applied [38, 39]. Stage 3 includes some steps namely; co-occurrence analysis, Co-authorship Analysis, Citation Analysis, bibliographic coupling analysis, and citation network. Stage provided a comprehensive review of solution methods and basic concepts. The last stage, stage 5, of this paper provides results and discussion that will answer the above-mentioned research questions. The stage 5 will discusses the findings and identify important gaps and some future directions will be proposed (Table 1).

To have better understanding the research field in this study and to provide new insights from publications, the information provided in this work tries to reply the below questions:

- What are the main topics and keywords regarding solar energy and supply chain?
- Which journals have the most contributions in the field? Who are the best researchers in the area? And what is the country origin for these researchers?
- What is the basic concept of solar renewable energy supply chain? And why solar energy is important?
- What are the different forms of renewable energy? And which field of renewable energy are most important part?
- Which solution approaches have been used mostly?
- What are the current gaps and future trajectory in the area?

3 Bibliometric Analysis

Scientometric analysis is the field of study that measure and analyze the literature, scientifically [40]. Bibliometrics is the most famous field of scientometric that use statistics to analyze and measure the impacts of book, research articles, conference papers, etc. [41]. Recently, this field of analysis has been attracted by researchers and has been used in different literature review fields [42–45]. The following sub-sections provide a new insight of bibliometric analysis in the area. Figure 1 presents distribution of published documents by subject area. From Fig. 1, Energy, Engineering, and Material Science have the most contributing in the area while Mathematics, Chemical Engineering, and Computer Science possess the least contributing in the field.

3.1 Keywords Analysis

Figure 2 presents sum of times cited per year for published documents. As it is clear from Fig. 2, sum of citation were increased until end of 2019, fairly; and then dropped by 16% in 2020. In 2007, the number of citations rose 171% and then less sharply until 2019; at this point, 2019, the number of citations decreased slighlt, -16%. In conclusion, Fig. 2 shows that number of citations was increased until 2019. Also, Fig. 3 presents a treemap visualization of different categories found by WOS. As it can be seen from Fig. 3, energy fuels (130), green sustainable science technology (68), environmental sciences (52), environmental engineering (30), and chemical engineering (28) are among top categories in the area while chemistry (11), economics (13), and materials science multidisiplinary (18) possess the least contribution in the field.

3.2 Network visualization

Keywords show the basic parts of a certain field of research, and could offer a sight of the knowledge organization. Figure 4 depicts a keyword co-occurrence analysis by a network map that each node in the network display a keyword, and

Table 1 Research methodology

Stage #	Steps	Sub-steps
Stage 1 Documents from databases	Step 1 select database Step 2 filter i. Keywords: solar energy supply chain ii. Type of documents: only articles (no Book, Chapters, no Chapters, no Reviews or Conference papers)	Step 1.1 Scopus is selected as database Step 1.2 Total 305 documents are found.
Stage 2 Check for duplicate documents	Step 1 use mendeley to filter documents	Step 1.1 Research Questions
Stage 3 Using social network analysis	Step 1 Use VOSviewer to analysis text	Step 1.1 i. Co-occurrence analysis ii. Co-authorship analysis iii. Citation analysis iv. Bibliographic coupling analysis v. Citation network
Sage 4 Comprehensive review	Step 1 a comprehensive overview	Step 1.1 i. General illustration ii. Mathematical modeling iii. Comparison
Stage 5 Results and discussion	Step 1 i. Answer the research questions	Step 1.1 i. Findings ii. Identify gaps & future directions

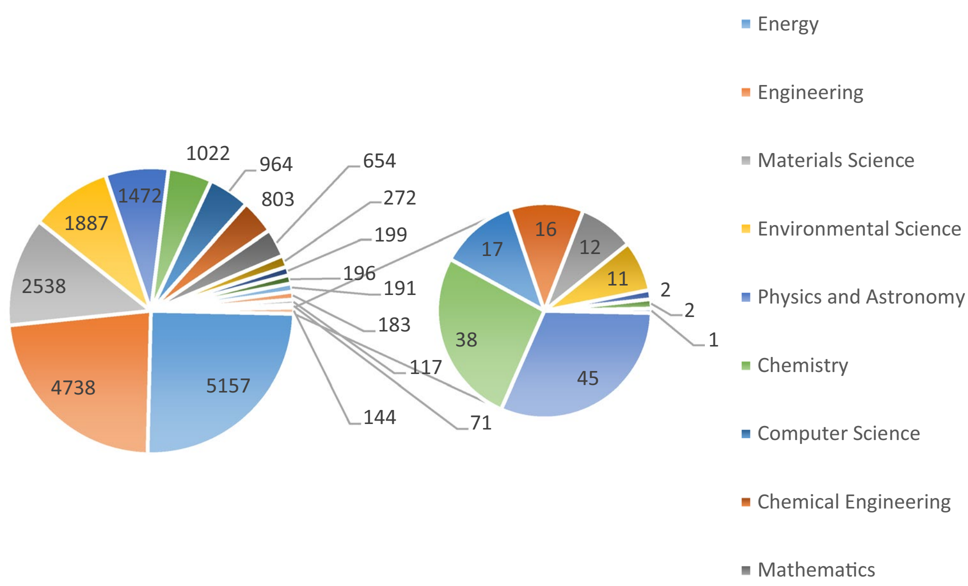

Fig. 1 Published documents by subject area

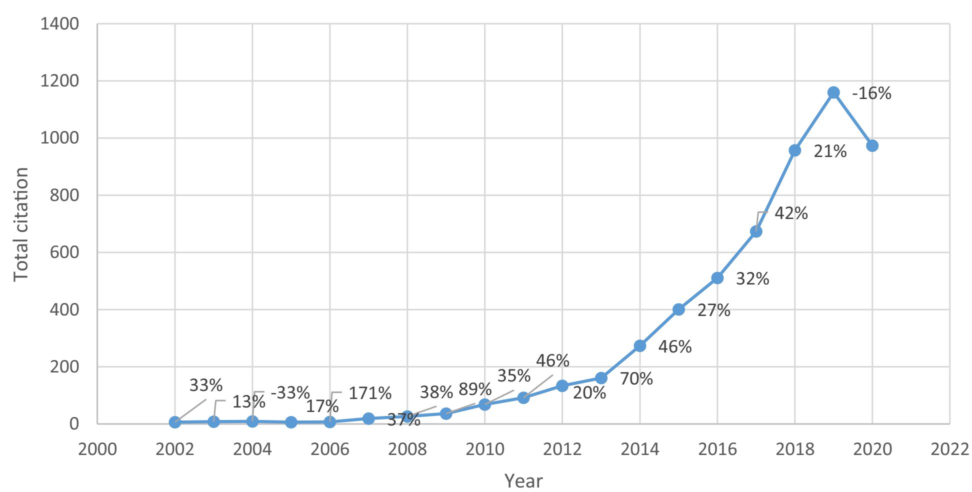

Fig. 2 Sum of times cited per year including percentage change

the link between the nodes illustrates the co-occurrence of the keywords. From Fig. 4, supply chain, computer simulation, markov processes, life cycle, life cycle assessment have been interested by researchers, recently. The color of each circle presents the identified cluster and size of each circle importance of the keywords meaning those keywords with big size circles have been used more than others. The green and yellow colors show the keywords that have been used recently while dark blue color are those have been used at beginning of the horizon time (around 2012).

Table 2 presents top and important keywords in each cluster. The mentioned clusters have been found by VOSviewer software resulting in, in total, 11 clusters; and for each cluster, 2 top keywords have been presented. Figure 5 depicts a citation network map presenting authors' name. Again, the color of circles shows the clusters and each cluster represent the last name of most cited authors over the horizon times (1999–2020). The parameter settings for Fig. 5 have been provided by Table 3. The settings, in Table 3, have been provided by default. Figures 6 and 7 represent item and cluster density visualization based on keywords occurrences, respectively. In Figs. 6 and 7, light colors show keywords with the most occurrences while dark colors illustrates keywords with the least occurrences. Supply chain, photovoltaic system, solar energy, power supply, power conversion efficiencies, and renewable energy have most occurrences.

3.3 Bibliographic coupling

When two documents reference another common documents in their references, bibliographic coupling occurs [46, 47]. Figure 8a–d show bibliographic coupling over found documents in the databases (WOS). Figure 8a and b illustrate network visualization and overlay visualization bibliographic

Fig. 3 Treemap visualization of different categories (database: WOS)

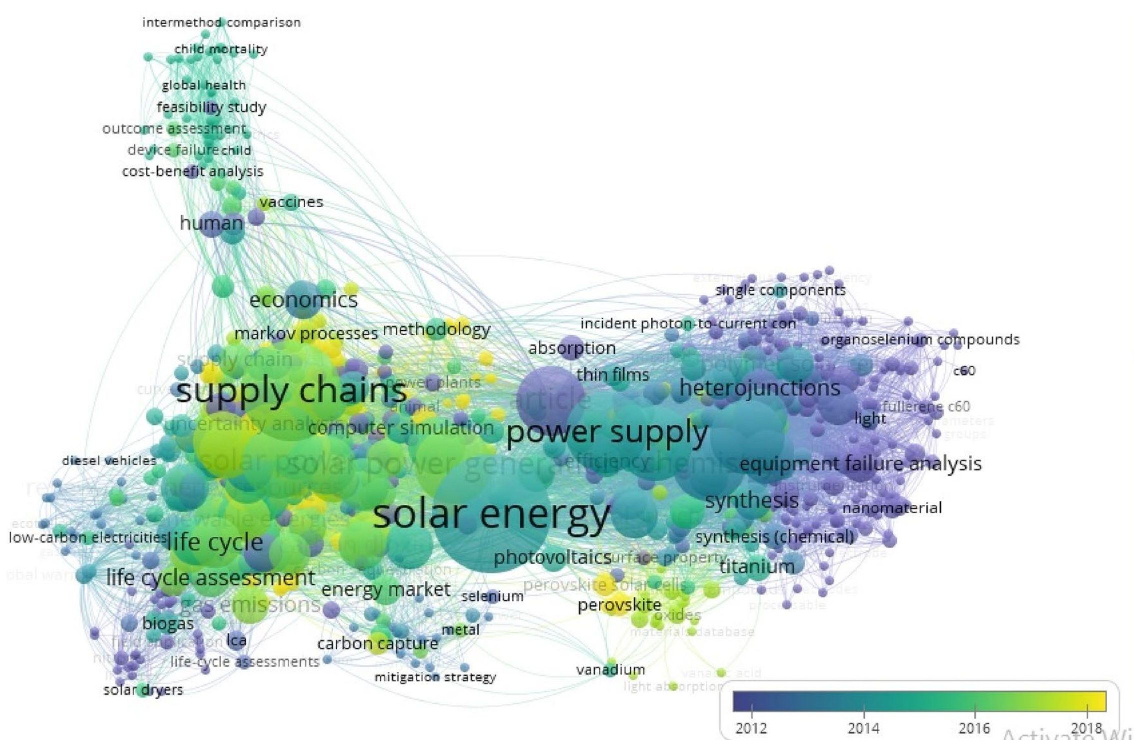

Fig. 4 Overlay visualization occurrences

coupling. It can been observed from Fig. 8a and b that most bibliographic coupling occurred prior to 2016. Also, Fig. 8c and d present network and overlay visualization bibliographic coupling organization on the horizon time; school of industrial engineering, department of civil engineering, and advanced mining technology center possess the most contribution in the area, recently (2020). Figure 9 shows density visualization of bibliographic coupling based on item density sources. As it is clear from Fig. 9, Renewable Energy, Advanced Materials Research, and Applied Mechanics & Material are three major sources. Table 4 represent a summary of literature review in the field. Researchers have focused on solar energy, along with hybrid renewable energy systems. Carbon emission, supplier evaluation and selection,

Table 2 Top Keywords in each cluster

Cluster	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Item 1	Electric power systems	Chemistry	Biogas plant	Material testing
Item 2	Power plant	Power supply	Bio-waste	Small molecules
Cluster	Cluster 5	Cluster 6	Cluster 7	Cluster 8
Item 1	Developing country	Particle size	Equipment failure analysis	Computer simulation
Item 2	Cost-benefit analysis	Polymer brushes	Large effective	Biocathode
Cluster	Cluster 9	Cluster 10	Cluster 11	
Item 1	Battery storage	Computational studies	Chains	
Item 2	Cost reduction	Hybrid materials	Electronic structure	

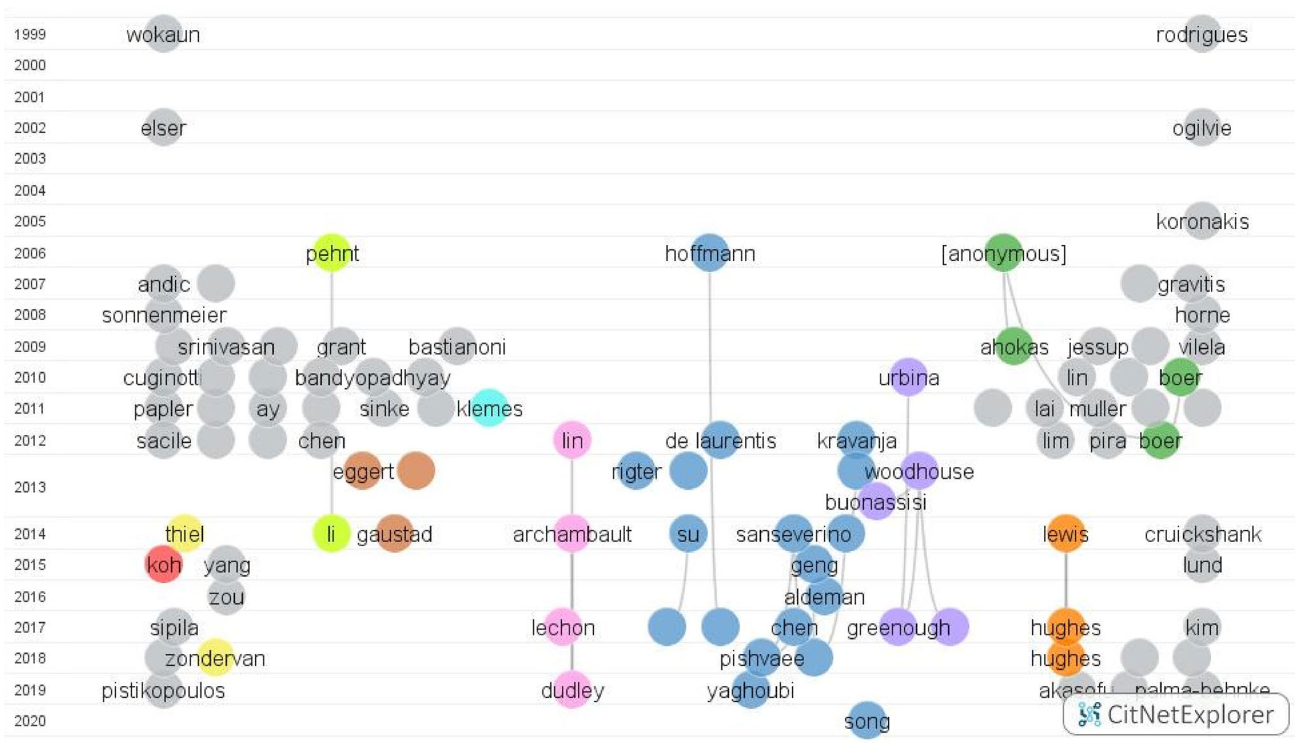

Fig. 5 Citation network

Table 3 Parameter settings for Citation Network (38 have been identified)

Clustering parameters	Values
Minimum number of citation	10
Minimum cluster size	1
Number of random starts	1
Number of iterations	1000

techno-economic assessment, reducing environmental footprint, and energy storage are most common problems in the literature. From Table 4, in terms of methodology, ANP, mixed integer programming, game model, and life cycle assessment are most interested methods that have been applied by researchers.

4 Optimization Solution Methods

This section provides the optimization solution approaches applied to supply chain of solar energy. Figure 10 classifies the most important optimization approaches that have been applied to the above-mentioned problems. The approaches are classified into two general groups namely, mathematical optimization algorithms and metaheuristics. There are

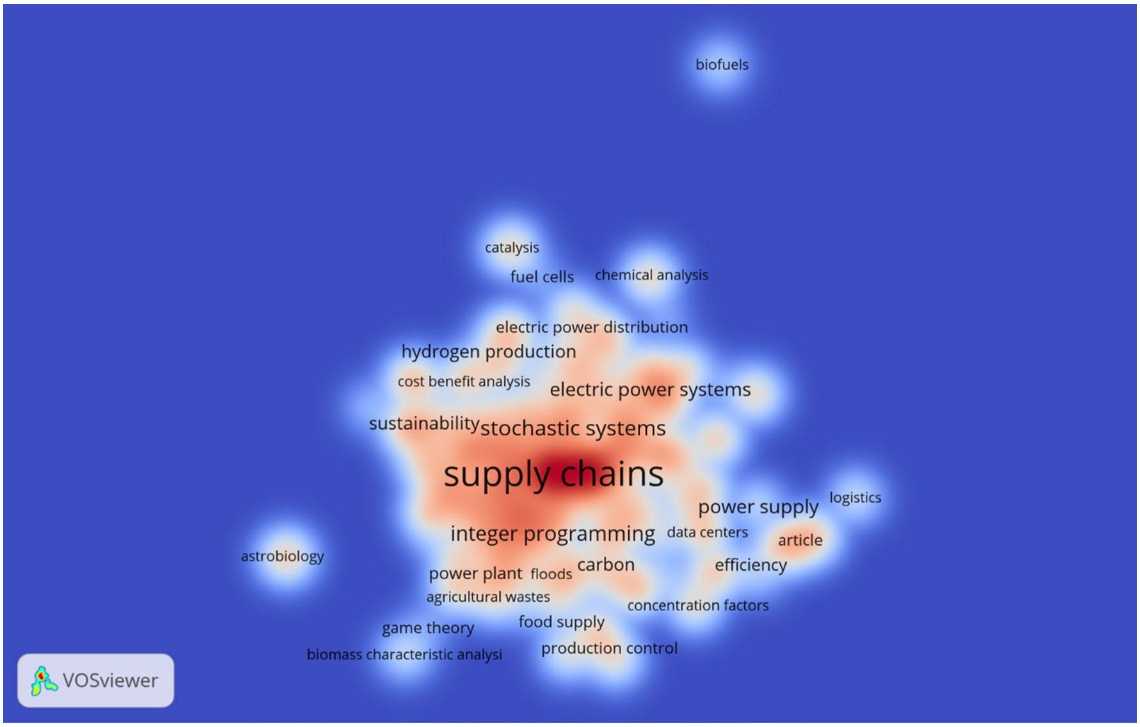

Fig. 6 Item density visualization (occurrences)

advantages and disdvantages for using different approaches as solution methods. As for metaheuristics, the important remark is that the goal of meta-heuristics is to search for and find suitable solutions rather than guaranteed optimal solutions. Consequently, if the model is simple enough to allow mathematical solution approaches, for example decomposition algorithms to achieve an optimal solution, then it is not necessary to use metaheuristic algorithms. Moreover, one of the disadvantage of metaheuristics is that many parameters must be set by the decision-maker rather than by mathematical algorithms, however metaheuristic solution methods can produce alternative optimal solutions in a single run. The mathematical optimization algorithms include discrete event-simulation, Monte Carlo simulation, mixed integer linear programming, Benders decomposition algorithm, Branch and Bound, column generation, and dynamic programming; and metaheuristics consist genetic algorithm, NSGA-II, simulated annealing, Tabu search, ant colony optimization, and particle swarm optimization. The following sub-sections provide the details for each solution approach.

4.1 Discrete Event-Simulation (DES)

DES models are the mission of a system as a discrete order of events in time [69]. Some examples of DES models in solar energy supply chain are found in [70–72].

4.2 Monte Carlo Simulation

Monte Carlo method is a wide range of computational calculations, which depend on repeated random examination for gaining numerical results. The essential idea of Monte Carlo method is to apply randomness to discussed problems, which might be deterministic on an elementary level [73]. Some of instances of Monte Carlo method in supply chain of solar energy are available in the works of authors of [74–79].

4.3 Column Generation

The overall idea of column generation is that several linear programs are excessively large for every factor to be measured obviously. Because of the fact that large variables of the factors will be not necessary, only a subset of factors will be measured, when considering the problem [80]. Some studies of column generation applied to solar energy supply chain are found in [81–83].

4.4 Dynamic Programming (DP)

DP refers to disentangling a complex problem by separating it into less difficult sub-problems in a recursive method [84, 85]. The works of the [86–93] are instances of application of dynamic programming method in supply chain of solar energy.

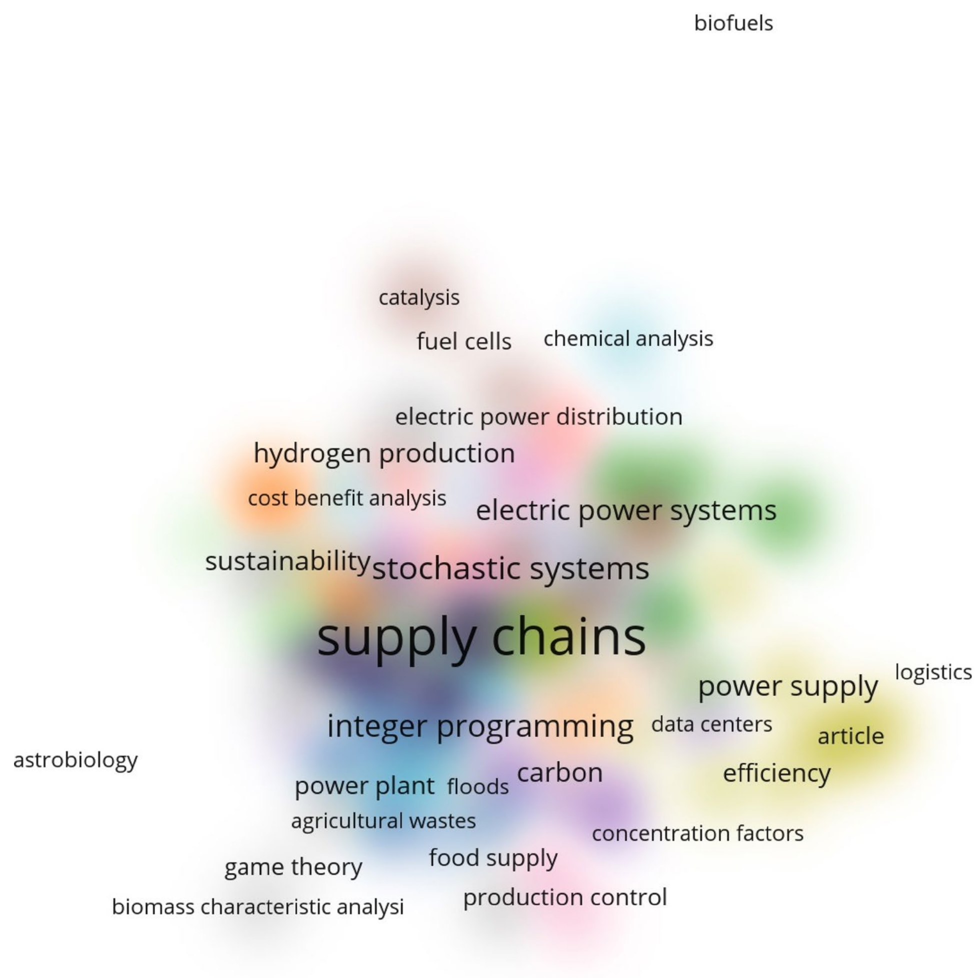

Fig. 7 Cluster density visualization (occurrences)

4.5 Mixed-Integer Programming (MIP)

MIP is a mathematical optimization in which some of the variables are integer and others are not discrete [94–97].

4.5.1 Branch and Bound (B&B)

B&B is an algorithm paradigm suitable for discrete and combinatorial optimization problems that enumerate the candidate solutions using state space search, systematically [98–102].

4.6 Metaheuristic Approaches

Metaheuristic is a higher-level heuristic method that design, generate, or select a heuristic solution to an optimization problem [103, 104].

4.6.1 Heuristic Search

In case classic methods are too slow or are not able to find exact solution, heuristic methods could be proposed [105–107].

4.6.2 Genetic Algorithm (GA)

GA is an evolutionary approach motivated by nature, which belongs to the metaheuristic family [108–117].

4.7 Multi-objective Optimization (MOO) Approaches

MOO approaches are fields of optimization that include more than one objective function to be optimized simultaneously [118–122].

4.7.1 Goal Programming (GP)

The GP method, is a division of MOO techniques and is an extended version of linear programming for solving MOO problems [123]. The application of goal programming in supply chain of solar energy could be found in [124–130].

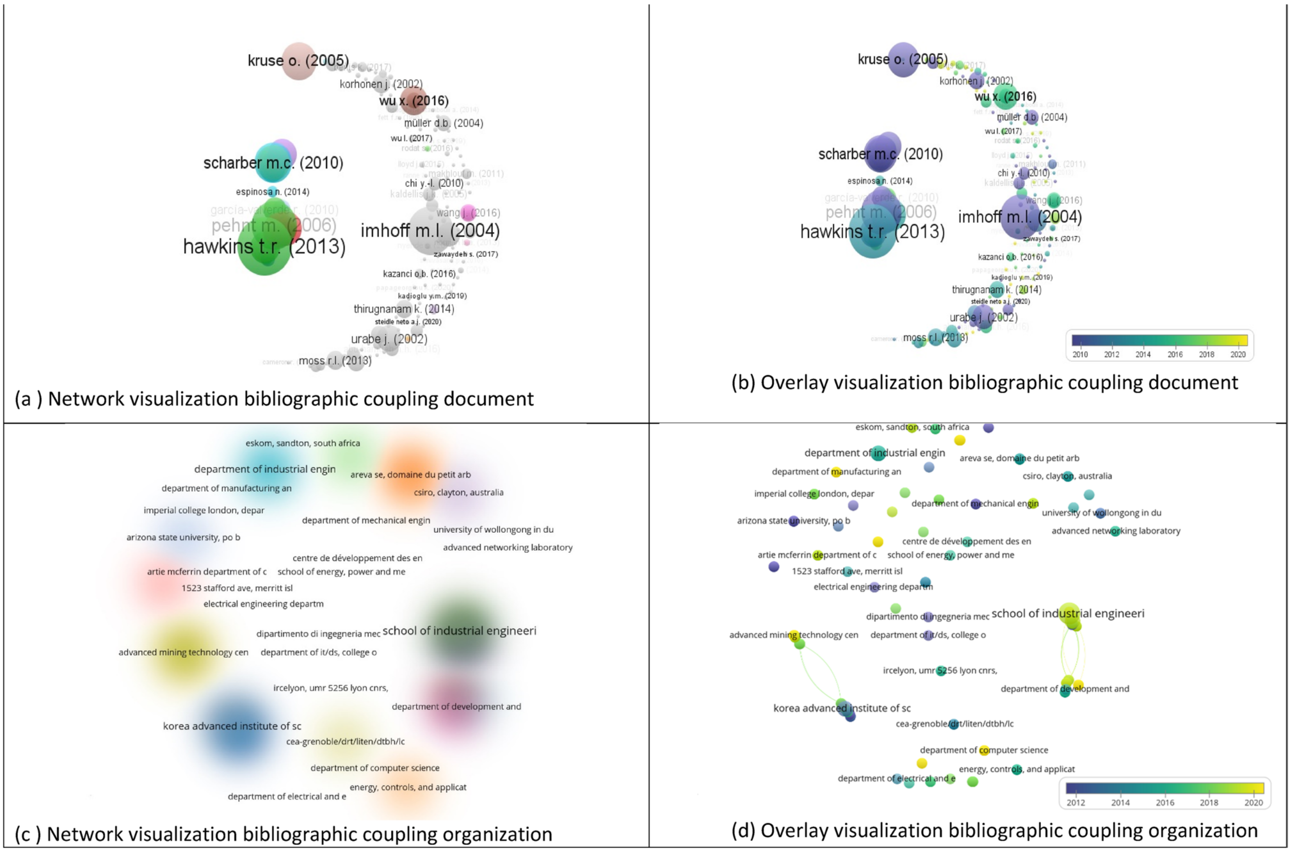

Fig. 8 Bibliographic coupling (network and overlay visualization)

Fig. 9 Density visualization bibliographic coupling (item density sources)

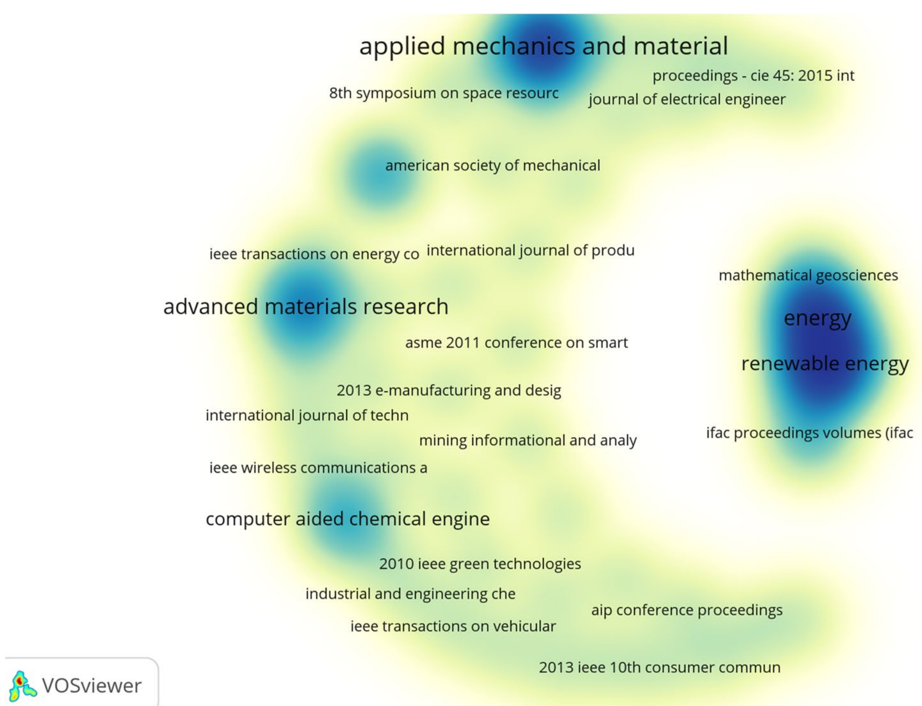

Table 4 Summary of literature review

Source	Problem	Objective	Methodology	Results and findings
[48]	Negative impact of CO_2 emission on electricity prices	Assessing impact of renewable production on electricity prices	Two-regime Markov switching model	Inducing a negative marginal effect. Hybrid systems have a noteworthy influence on the distribution of prices
[49]	Low carbon supplier selection	Solving supplier selection problems regarding the alternatives and criteria.	Integrating the SPAN and the ANP under fuzzy linguistic environment	The practicability of the proposed model has been approved by a solar power company
[50]	Bad weather, heavy snow, sand or dust storms in deserts in China	Generating electricity in China and the levelized electricity costs.	Simple mathematical model [51]	Levelized electricity cost of the suggested model is competitive with that of clean coal power plant
[52]	Reducing using the industrial system's virgin resource.	Discussing the product-based systems and geographical approaches in industrial ecology.	An application of the product-based systems method and a basic life cycle inventory model	Supporting conflicting decisions for environmental policy and management
[53]	Techno-economic assessment.	Evaluating the flexibility of the Bolivian power generation system	Using an open source unit commitment and (Dispa-SET)	A hybrid renewable system than 30% is technically feasible
[54]	There are gaps within the green supply chain and act on strengthening	Identifying some weaknesses in the Welsh energy system	Investigating the regional innovation system of Wales on green innovation	The findings show that regional government is playing a significant role
[55]	Increasing adoption of clean technology processes	Examining the supply chain integration, and product modularity as antecedents of the market valuation	The research used the SEM-PLS to analyze the data gathered from the firms	The results of the study present that the aggregated product modularity changes the supply chain flexibility
[56]	Reducing their environmental footprint	Achieving perceptions in internal operations and improving organizational procedures	Life cycle assessment (OLCA) method	The environmental influence profile is dominated by transport activities
[57]	Improving reliability of power grid and reducing the risk of failure	Proposing a solar generation model based on the Markov Chain	Markov chains are continuously trained by historical records	Findings approve the accuracy of the proposed model
[58]	Using greater heating value than the conventional fuels possessing zero carbon emission	Developing a general optimization model applying for vehicle fueling and electricity generation	A mixed-integer linear programming model is addressed	The optimal configuration of hydrogen supply chain and the associated cost identified
[59]	Thermal-hydraulic process	Using low-grade thermal energy for thermal-hydraulic conversion	Using two different levels of temperatures and fluids	Reducing the electrical consumption and overall greenhouse gas emissions
[18]	Multi-criteria life cycle assessment	Proposing a global coverage of environmental performance of PV systems	Using ENVI-PV	The performance outperfprms in different spatial and techno-economic contexts
[60]	Sustainable silicon photovoltaics manufacturing	Optimizing supply chain layouts for PV manufacturing	Using techno-economic integrated tool for tariff and transportation	Results show that introducing tariffs considerably increase the minimum sustainable price
[61]	Two-echelon multi-period multi-product solar cell supply chain considering different scenarios	Optimal scenarios for solar supply chain	Game model	The results estimate the necessary number of solar panels in each period
[62]	Supplier evaluation and selection	Analysis the development and characteristics of the solar thermal application industry	Using quality-oriented product lifecycle management model	The results show that the study contributes theoretically and practically to guiding global competition
[63]	Energy storage and electricity production	Providing energy storage and support the development of biomass production	A techno-economic model is proposed	The results show that the LCOE for solar PV and using woody biomass feedstocks is competitive with lithium-ion batteries

Table 4 (continued)

Source	Problem	Objective	Methodology	Results and findings
[64]	Power supply chain network design problem	Maximizing benefits for both the companies and users in smart grid supply chain	Differential pricing and buy-back policies	The findings present that the centralized model is significantly better than the decentralized model
[65]	Reducing carbon emission of supply chain	Promoting public transport european transport sector	Installing solar panel	Results show energy efficiency and cutting GHG emissions associated with freight and passenger transport
[66]	Transformation of the energy industry	Examining the strategic approach of incumbent firms in the oil and gas industry	several case studies have been conducted within three largest oil and gas firms	The results show that companies have problems with integrating solar PV technology in the supply chain
[67]	Market access barriers in alternative energy	Analyzing the influence of domestic politics on trade disputes	Two-level game method	Domestic policy constrains Washington's ability to effect Chinese policies
[68]	Inventory fluctuations, lack of raw, and geopolitical tensions	Investigating the photovoltaic supply chain, building a framework	Critical PVSC constituents are compared and contrasted with traditional SC typologies	Management of the PVSC

4.7.2 Markov Decision Process

This method provide a framework in situations some part of outcomes are random and some parts are under control of decision makers. Some examples of this method in solar energy supply chain could be found in: [131–136].

4.7.3 Constraint Programming

Constraint programming is a famous technique for solving combinatorial optimization problems that state the constraints on the feasible solutions of decision variables [137]. More details for application of constraint programming in solar energy supply chain could be highlighted in the works of [138–142].

4.7.4 Simulated Annealing

Simulated annealing is metaheuristic approach based on probabilistic techniques for approximating a global optimum of given function [143, 144]. In the works of the [145–151] some instances of the simulated annealing could be found.

4.7.5 Tabu-Search

Tabu-search is a metaheuristic local search method to find local optimum of a given function [152, 153]. Recent publications of integration of tabu search method and solar energy are available in [154–157].

4.7.6 Ant Colony Optimization (ACO)

ACO motivated by behavior of real ants and is a method for solving optimization problems by finding good paths through graphs [158, 159]. Some works in the area of ant colony optimization applied to solar energy is available in [160–167].

4.7.7 Particle Swarm Optimization (PSO)

PSO is a computational method applied to combinatorial optimization problem by improving a candidate solution, iteratively [22]. More example of particle swarm optimization with focus on solar energy are available in [121, 168–172].

4.7.8 Non-dominated Sorting Genetic Algorithm (NSGA-II)

A fast and elitist multiobjective genetic algorithm known as non-dominated sorting genetic algorithm (NSGA-II) recommended by Deb et al. [173] has been applied to various MOO problems. Some of recent publications applied to solar renewable energy supply chain are available in [174–179].

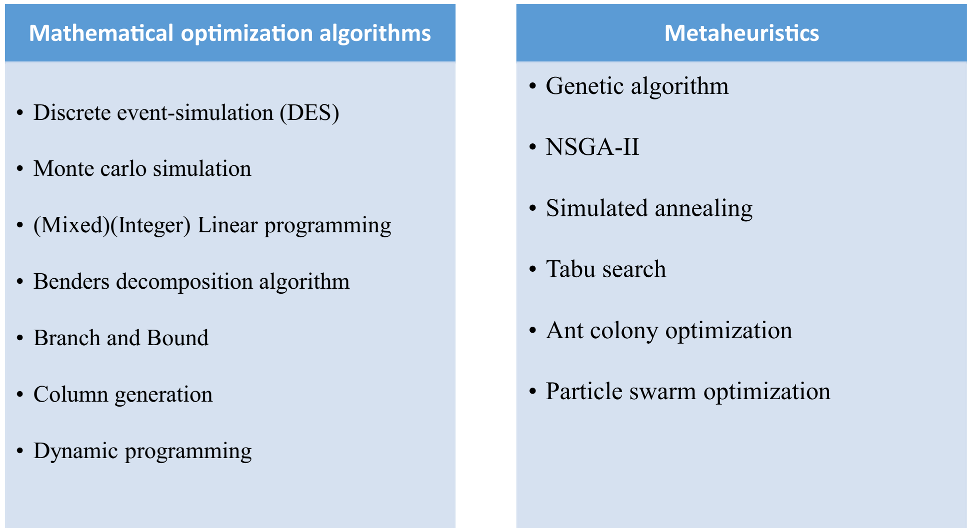

Fig. 10 Solution approaches applied to supply chain of solar energy

5 Statistical Analysis on Solution Approaches

As mentioned above, there are several optimization methods that have addressed in literature to solve the supply chain of solar energy. There are different classification for solving optimization problems, however, mostly it is discussed exact and metaheuristic approaches. Metaheuristic approaches mostly find good solution rather than guarantee optimal solution; in case the optimization problem is simple enough to solve it with a mathematical method, there is no need to use metaheuristic solution methods. Conversely, metaheuristic approaches produce alternative optimal solutions in a single run [180–182]. In terms of MOO problems, most of exact solution approaches convert MOO problems to a single optimization one while metaheuristic methods solve the MOO problems without converting to a single objective optimization problem. Figures 11 and 12 provide a details analysis of the most famous methods applied to supply chain of solar energy. Among the published documents in the field, 93.17% of total studies are single-objective optimization problems while 6.83% of published documents include multi-objective optimization problems. In terms of single-objective optimization, monte-carlo and dynamic programming

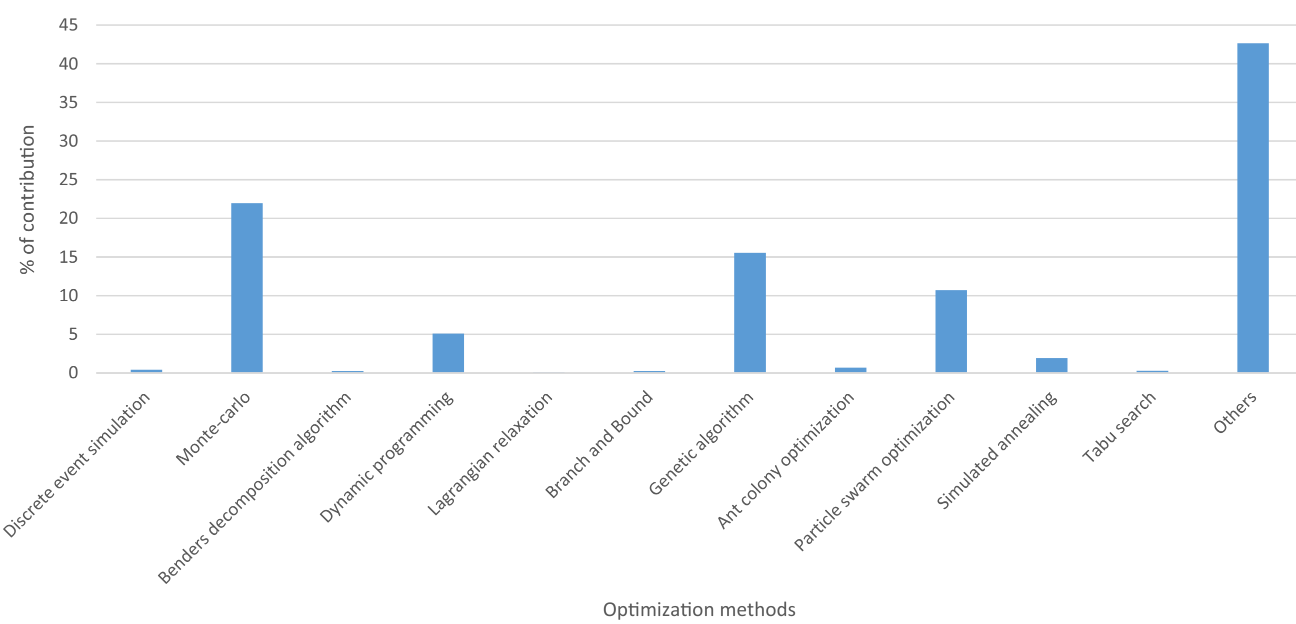

Fig. 11 Single objective optimization methods

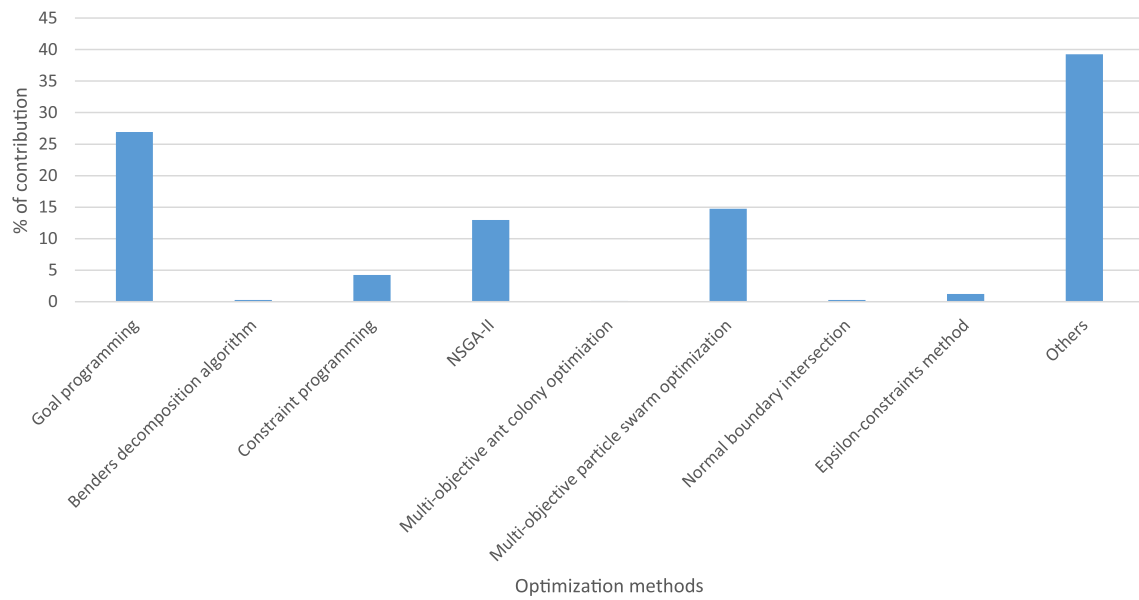

Fig. 12 Multi-objective optimization methods

methods are the most famous mathematical methods with 21.96% and 5.06% applicability and genetic algorithm and particle swarm optimization have contributed about 15.58% and 10.71% and are the most famous metaheuristic approaches. On the other hand, in terms of MOO, goal programming has contributed about 26.91% and has highest contribution in the area followed by multi-objective particle swarm optimization (14.75%), NSGA-II (1297%) and constraint programming (4.23%).

6 Conclusion and Directions for Future Study

This study aimed to review the most important renewable energy supply chain models for and provides a short analysis of published literature. This paper highlighted the most important subject areas by keywords analysis. Moreover, several criteria were identified that could help researchers for future works. Furthermore, this paper may help researchers to identify important gaps in the research area and, subsequently, develop new models in the area. A detailed scientometric analysis was performed as an influential tool for use in bibliometric analyses and reviews. For this aim, keywords and subject areas are discussed, and review on problems and research methodology are provided in the second section of the work.

This study describes some key arguments that are worthy of further discussion:

- In terms of the subject area, energy fuels, green sustainable science technology, environmental sciences, environmental engineering, and chemical engineering are most discussed areas addressed by scholars.
- In terms of keywords analysis, trends present that studies on renewable energy will increase in future. Moreover, supply chain, computer simulation, markov processes, life cycle, life cycle assessment are examples the most common keywords that have been used by researchers.
- Carbon emission, supplier evaluation and selection, techno-economic assessment, reducing environmental footprint, and energy storage are most common problems in the literature.
- Among the current approaches exact algorithms are the top methods that were used by researchers.
- The majority of studies are deterministic approaches, while there is an urgent need to provide robust approaches for tackling uncertain situations.
- 93.17% of total studies are single-objective optimization problems while 6.83% of published documents include multi-objective optimization problems.
- In terms of single-objective optimization, monte-carlo and dynamic programming methods are the most famous mathematical methods with 21.96% and 5.06% applicability and genetic algorithm and particle swarm optimization have contributed about 15.58% and 10.71% and are the most famous metaheuristic approaches.
- In terms of multi-objective optimization, goal programming has contributed about 26.91% and has highest contribution in the area followed by multi-objective particle

swarm optimization (14.75%), NSGA-II (1297%) and constraint programming (4.23%).
- Energy fuels, reen sustainable science technology, environmental sciences, environmental engineering, and chemical engineering are among top categories in the area while chemistry, economics, and materials science multidisiplinary possess the least contribution in the field.

For future research directions, a comprehensive review in other renewable energy sources, such as biomass, wind, and marine are encouraged. Moreover, more studies addressing the development of novel and hybrid approaches should be investigated. Furthermore, at the time of writing this paper, we had access to only a limited number of published articles by Scopus and WOS. However, the most important parts of this paper are the keywords and bibliometric analysis that considers the whole database, from which we chose some examples of published articles for review. Therefore, a more comprehensive review in the research area is suggested, which could be focus in a specific area such as solar energy or supply chain of renewable energies. Also, since the hybrid renewable energies are interesting could be a promising topic for the future work as a review. In addition, using forecasting methods such as neural network for prediction is interesting topic [183, 184], which could be used in the field.

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Declarations

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