The Contribution of Bottom-Up Energy Models to Support Policy Design of Electricity End-Use Efficiency for Residential Buildings and the Residential Sector: A Systematic Review

Genoveva Vargas-Solar, Marlene Ofelia Sanchez-Escob, Julieta Noguez, Jos Martin Molina-Espinosa, Rafael Lozano-Espinosa, Carlos Henggeler Antunes, Javier Reneses

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Review

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Marlene Ofelia Sanchez-Escobar [1,*], Julieta Noguez [1], Jose Martin Molina-Espinosa [1], Rafael Lozano-Espinosa [1] and Genoveva Vargas-Solar [2]

[1] Tecnologico de Monterrey, School of Engineering and Science, Ave. Eugenio Garza Sada 2501, Monterrey 64849, NL, Mexico; jnoguez@tec.mx (J.N.); jose.molina@tec.mx (J.M.M.-E.); razolano@tec.mx (R.L.-E.)
[2] LIRIS UMR5205, CNRS, 69621 Villeurbanne, France; genoveva.vargas-solar@liris.cnrs.fr
* Correspondence: A00704709@itesm.mx; Tel.: +521-5544995733

Abstract: Bottom-up energy models are considered essential tools to support policy design of electricity end-use efficiency. However, in the literature, no study analyzes their contribution to support policy design of electricity end-use efficiency, the modeling techniques used to build them, and the policy instruments supported by them. This systematic review fills that gap by identifying the current capability of bottom-up energy models to support specific policy instruments. In the research, we review 192 publications from January 2015 to June 2020 to finally select 20 for further examination. The articles are analyzed quantitatively in terms of techniques, model characteristics, and applied policies. The findings of the study reveal that: (1) bottom-up energy models contribute to the support of policy design of electricity end-use efficiency with the application of specific best practices (2) bottom-up energy models do not provide a portfolio of analytical methods which constraint their capability to support policy design (3) bottom-up energy models for residential buildings have limited policy support and (4) bottom-up energy models' design reveals a lack of inclusion of key energy efficiency metrics to support decision-making. This study's findings can help researchers and energy modelers address these limitations and create new models following best practices.

Keywords: energy modelling; electricity efficiency; energy policy; residential buildings; households; data-driven approach

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1. Introduction

The 2019 world energy outlook anticipates that the building sector (including households and services) will continue being the main contributor to global electricity demand by 2040 [1]. Alone households expect a 60% increase in electricity consumption in developing economies. The outlook associates the possible increment in the buildings' electricity demand by utilizing more air conditioners, household appliances, and electric vehicles. On the other hand, since the increase in energy use is related to the increment of carbon dioxide (e.g., CO_2) emissions, it is advised in the literature to enhance the efficiency of electricity use [2]. Thus, it is possible to reduce emissions without compromising the development of electricity services. To this end, governments design policies that promote electricity end-use efficiency [2] with the support of bottom-up energy models [3].

Policy design refers to the selection of policy tools to achieve energy efficiency objectives [4], eliminate barriers toward efficiency, and gain energy efficiency benefits [5]. The design of policies for electricity end-use efficiency focus on the factors that distort market and restrict the adoption of efficient technologies [2]. For instance, expected short payback period on investments, uncertainty about actual savings, the lack of trained people to invest in energy efficiency, physical barriers of the technology, attributes that affect performance, and unfavorable investment due to lower average usage of the product [2]. Besides, the creation of policies is a process that includes two steps [6]: (1) policy definition and (2) policy instruments development. The first involves the definition of objectives, strategies to be used for distinct groups, and the legal and regulatory frameworks; in contrast, the second includes the creation of incentives, penalties, standards, as well as technical and financial support. A complete description of policy instruments is available in [7] and summarized in Table 1.

Table 1. Energy Efficiency Policy Instruments.

Type of Instrument	Instrument	Description
Market-based	Energy Taxes	Impact the price of goods and services that generate high greenhouse emissions or the price of the emission itself [8].
	Tradable emissions permits	Limited emission permits are divided among companies that pollute to control the amount of emissions agreed by regulatory agencies [9].
	White certificates schemes	Energy suppliers commit to (1) Promote energy efficiency in final uses and (2) implement interventions to save a percentage of their distributed or supplied energy [10].
Financial incentives	Subsidies	Direct payments or tax rebates are used to motivate expenditure on energy efficiency [7].
	Access to capital measures	Grants and loans are provided to drive specific energy efficiency expenditures [7].
Regulatory Measures	Codes and Standards	Building codes and energy performance standards [7] are used to impose the compliance of minimum energy efficiency levels to products or services (e.g., building design or construction [11]).
Information and Feedback	Information	Certificates, labels, or audits are used to avoid suboptimal energy efficiency investments [7].
	Feedback	Consumption and energy information is given to consumers to promote energy conservation [12].
Non-regulatory measures	Voluntary Agreements	Adjustable agreements among firms and public authorities used to increase energy efficiency and diminish greenhouse emissions [13].

In this context, policy-makers rely on energy models to estimate the impact of policy [14] and technology choices [15], to control energy consumption [16], and to enhance energy efficiency levels [17]. The literature classifies energy models by their analytical approach as top-down or bottom-up [15,18–20]. Top-down models use aggregated data to analyze synergies among sectors (e.g., energy sector versus demand sector). While bottom-up models only focus on describing energy end-uses and technological choices using disaggregated data [20]. In the research, we examine bottom-up models since we are interested in the modeling of end-use energy efficiency that support policy design. Therefore, we present a taxonomy [18–22] of bottom-up energy models to identify their main characteristics and how these features relate with the support to policy design.

The classification describes bottom-up energy models with the following attributes [20,21]: (1) *sector coverage*, which specifies how many sectors the model includes (e.g., multi-sector or single-sector) [20]. The first are concerned with the impacts of diverse factors (e.g., policies, technologies, or others) in different sectors [23]. While, the second focus on the effects in only one of them. The following sectors can be included in models [23]: economic sector, which includes energy and production sectors, and demand sector (i.e., energy consumption sector) that include: households, buildings, industries, and transport sectors [24]; (2) *geographical coverage*, which defines the geographic level represented by the model (e.g., global, regional, national, local or project) [20]); (3) *time horizon* which determines the time-frame where the model is applied [21]. For instance, models can represent the evolution or configuration of energy systems in the short, medium, or long term [20]; (4) the *methodology* which indicates the modeling approach used for the model's design (e.g., economic, optimization, simulation, spreadsheet, back-casting, and multi-criteria) [20]; (5) the *programming technique* which specifies the mathematical or non-mathematical approach used to create the model (e.g., linear, dynamic, heuristic, or other); (6) the *end-use energy modeling technique* which determine the technique(s) used to represent end-uses in models (e.g., engineering and/or data-driven) [18,19]; (7) the *data time split* which represents the model's time resolution of the input data (e.g., hourly or minute, weekly, monthly, and yearly) [22]; (8) the presence of *metrics and tools* that ease energy-efficiency policy design (e.g., cost, CO_2 emissions and scenarios) [25–27]; and finally (9) the residential electricity end-uses implemented by the model (e.g., Appliances (A), Space Heating(SH), Space Cooling (SC), Lighting (L), Water Heating (WH), and Cooking (C)). The complete taxonomy with more detail is available on Table 2.

Nevertheless, scholars question the support towards the design of energy efficiency policies that these models provide; especially, for residential buildings [3]. Likewise, the literature reveals the following limitations of these kinds of models [3,30]: (1) the implementation of energy efficiency is not straightforward, (2) the models do not provide a portfolio of analytical methods, (3) they do not transform modeling results into concrete policy recommendations, (4) they oversimplify policy instruments, and (5) they do not capture the market and behavioral failures. Finally, research has not uncover a study that analyzes quantitatively these kinds of models.

The following review fills the gap by performing a quantitative analysis of bottom-up energy models. The study aims to reveal the contribution of bottom-up energy models towards policy design of electricity end-use efficiency. We examine the case of residential buildings (including households), given their importance in the energy consumption sector. In this study the term households and residential sector is used interchangeably. The following research questions determine what is studied in detail:

1. RQ1: What kind of bottom-up energy models aim to support policy design of electricity end-use efficiency for residential buildings and the residential sector, and how do they relate to specific policy instruments ?
2. RQ2: Which types of analytical methods are used in bottom-up energy models that aim to support policy design of electricity end-use efficiency in residential buildings and the residential sector?
3. RQ3: Which types of energy policies are supported by bottom-up energy models that aim to support policy design of electricity end-use efficiency in residential buildings and the residential sector?

The rest of the paper is organized as follows: Section 2 presents a brief literature review. Section 3 outlines the methodology to perform the review. Section 4 presents the results and discussion. Section 5 includes a comparison with other studies and findings; and finally, Section 6 presents conclusions and future work.

Table 2. Taxonomy of Bottom-up Energy models.

Category	Subcategory	Model Focus
Sector Coverage [20]	Single-Sector	Just one sector
	Multi-Sector	Interaction between sectors
Geographical Coverage [20]	Global	World economy/situation
	Regional	International regions
	National	All sector within a country
	Local	Regions within a country
	Project	Specific energy project
Time Horizon [20]	Short	Less than 5 years model
	Medium	5 to 15 years model
	Long-Term	Greater than 16 years model
Methodology [20]	Economic	Representation of economic and technical effects of alternative economic strategies
	Optimization	Optimization of choices on energy investment
	Simulation	Replication of a system operation in a simplified form
	Spreadsheet	Utilization of a flexible tool to generate customized energy models
	Back-casting	Creation of views of a desired future and identification of trends to be broken to achieve the future
	Multi-criteria	Inclusion of additional criteria to the model beyond economic efficiency
	Other	Other methodology
End-use Energy Modeling Technique [18,19]	Engineering	Calculation of energy consumption based on thermodynamics and heat transfer of all end-uses
	Data-driven statistical	Correlation of end-use features with its energy use using statistical techniques
	Data-driven AI-based	Correlation of end-use features with its energy use using artificial intelligence techniques
Programming Technique [21]	Linear Programming (LP)	Discover arrangement of activities to minimize or maximize a defined criterion
	Mixed Integer LP	Extension to LP programming which include detailed formulation of technical properties and relations in modeling of energy systems
	Dynamic	Discover optimal growth path through division of an original problem and optimization of sub-problems
	Heuristic	Manage high dimension optimization problems [28]
	Other	Other type of programming technique
Data Time Split [22]	Hourly/Minute	Hourly/Minute data resolution
	Daily	Daily data resolution
	Monthly	Monthly data resolution
	Yearly	Yearly data resolution
Metrics and Tools [20]	Metrics	CO_2 emissions and cost as outputs in the model
	Tools	Scenario utilization to show model's results
Residential Electricity end-uses [29]	A, SH, SC, L, WH, C	Detailed identification of electricity consumption, energy use and energy savings by end-use.

Note: Electricity end-uses: AL = Appliances and Lighting, SC = Space Cooling, SH = Space Heating, WH = Water Heating, A = Appliances, L = Lighting, C = Cooking.

1.1. Classification of Energy Models

Energy models are useful for prospecting future energy demand and supply and simulating policy and technology choices and their impacts on energy demand and supply [15]. Diverse authors classify energy models by their analytical approach as top-down or bottom-up [15,18–20]. Van Beeck [20] differentiates these models with the following key features: level of data aggregation, degree of endogenous behavior, and level of detail of technology representation. In this regard, top-down models use aggregated data to analyze synergies among sectors (e.g., energy versus demand). While bottom-up models only focus on describing energy end-uses and technological choices using disaggregated data [20]. For this Systematic Review, we will be analyzing bottom-up models since we are interested in models centered on end-use energy efficiency.

1.2. Bottom-Up Energy Models (Bottom-Up Energy Models)

According to Prina et al. [21] and Van Beeck [20], bottom-up energy models have the following characteristics: *sector coverage*, which specifies how many sectors the model can represent; *geographical coverage*, which defines the geographic level implemented in the model; *time horizon* which determines the time-frame where the model is applied [21]. For instance, models can represent the evolution (e.g., forecast of energy efficiency) or configuration (e.g., household operation in a smart-grid) of energy systems in the short, medium, or long term. The *model methodology* which indicates the type of procedure used in the bottom-up energy model's construction, and the *programming technique* which specifies the mathematical or non-mathematical approach used to create the model. Additionally, Abbasabadi et al. [18] and Ugursal et al. [19] introduce the *end-use energy modeling technique* as a feature to describe bottom-up energy models. Swan et al. [19] categorize models as statistical or engineering, while Abbasabadi et al. classify them as data-driven or simulation-based engineering. Moreover, based on Kannan et al.'s Intra-Annual Time Split [22], we define the *Data time split* feature. This last represents the model's time resolution of the input data. Finally, we categorize bottom-up energy models according to the availability of *metrics and tools* to ease policy design.

On the other hand, although Prina and Van Beeck coincide on the type of characteristics of bottom-up energy models, there are differences in concepts. For instance, Prina et al. characterize the geographical coverage as single-node or multi-node, while Van Beeck typifies it as global, regional, national, local, or project. Likewise, Van Beeck's methodologies include economic, econometric, spreadsheet, and backcasting, which Prina et al. neglect. Finally, Prina et al. consider non-linear and heuristics programming techniques, which Van Beeck does not specify.

For this systematic review, we create a merged taxonomy of bottom-up energy models based on the categorizations present in [18–22]. We include the most precise classification of each attribute to generate a complete and accurate denomination of these kinds of models. The merged taxonomy aims to represent relevant features of bottom-up energy models and allows models' cataloging for further analysis. Table 2 presents key characteristics of bottom-up energy models as a merged taxonomy.

1.2.1. Sector Coverage

We choose Van Beeck's [20] classification in the sector coverage case, including single and multi-sector models. Against Prina et al.'s categorization [21], that specifies the options: all sectors and one sector, ignoring the possibility to select more than one sector, but not specifically all existent sectors.

Multi-sector models are concerned with the impacts of diverse factors (e.g., policies, technologies, or others) in different sectors [23]. In contrast, single-sector models focus on the effects of only one of them. White et al. [23] describe the following sectors that can be included in a multi-sector model: economic sector, which includes energy and production sectors, and demand sector (i.e., energy consumption sector) that include: households, buildings, industries, and transport sectors [24].

1.2.2. Geographical Coverage

We decided to use Van Beeck's [20] geographical coverage, which includes: global, regional, national, local, and project models. Contrarily, Prina's centers on bottlenecks of energy transportation instead of the geographical scope represented in the model. The focus of each geographical coverage is present in Table 2.

1.2.3. Time Horizon

In [20], Van Beeck presents a simple time horizon classification with specific time frames expressed in years. In comparison, Prina et al. describe the time-span with time-slices, which could difficult the paper categorization. In this SR, we contemplate Van Beeck's that includes: short, medium, and long-term spans. See Table 2 for a description of the focus of each of them.

1.2.4. Programming Technique

We use Prina's [20] categorization of programming techniques used for model creation, given its completeness versus Van Beeck's. The merged taxonomy includes the following types of programming techniques: linear, mixed linear, dynamic, heuristic, and other types. Table 2 describes the focus of each of them.

1.2.5. Data Time Split

In [22], Kannan et al. define a categorization of Intra-annual time splits, which specifies the number of temporal divisions that the model manages (e.g., minutes, hours, weeks, or seasons). For our taxonomy, we represent the resolution of the model's input data with the following types of time splits: hourly or minute, weekly, monthly, and yearly.

1.2.6. Metrics and Tools

In this category, we focus on the availability of the following metrics: cost, CO_2 emissions metrics, and scenarios in bottom-up energy models. According to McNeil et al. [25], cost and CO_2 emissions are key energy efficiency indicators. So its presence in models oriented to energy efficiency policy design is necessary. In the same manner, experts consider that scenarios are useful tools for policy-making [26] and to provide scientific evidence to decision-makers [27]. In this study, we examine in which proportion bottom-up energy models include these metrics and tools.

This newly merged taxonomy allows the analysis of bottom-up energy models in a quantitative form and the comparison of energy models based on relevant features.

1.3. Energy Efficiency Policies and Policy Design

A second taxonomy is necessary to analyze bottom-up energy models according to the policy interventions they support. In this section, we define the following important concepts to achieve that goal: energy efficiency (EE), energy efficiency policy, and policy design.

Residential Energy End-Uses

We study in this SR energy end-uses since they allow a detailed identification of electricity consumption, which support detailed analyses of energy use and energy savings.

Energy end-uses are categorized by the International Energy Agency as [29]: Appliances (A), Space Heating(SH), Space Cooling (SC), Lighting (L), Water Heating (WH), and Cooking (C). For our analysis, we examine energy end-uses supported by models in the residential sector and residential buildings.

2. Literature Review

Few studies examine bottom-up energy models that support energy efficiency policy design in residential buildings and households. Besides, none focuses on electricity end-use efficiency or on evaluating how they support policy design. In this regard, Mundaca and Neij [3] review energy-economy models used for energy efficiency policy evaluation for households. Nevertheless, the authors consider one type of energy model, and the portfolio of analytics techniques presented is limited. Calvillo et al. [31] review energy efficiency modeling approaches using the TIMES energy system model. Although this study is focused on energy efficiency policy in the residential sector using engineering-economic models, it does not consider other existent modeling techniques and methodologies. Hong et al. present a review of applications of machine learning techniques for the Building Life Cycle [32]. The study categorizes the phases of a building life cycle and analytics techniques applied for different applications during each stage. However, the study does not show the perspective of energy efficiency policy design, and it focuses entirely on the portfolio of techniques. Afroz et al. [33] create a review of data-driven models to improve HVAC's energy efficiency systems (e.g., Heating, Ventilation, and Air Conditioning) in buildings. The revision categorizes and examines data-driven modeling for HVAC based on their applicability and performance. However: (1) the study is not focused on energy models applied to households or residential buildings, and (2) it does not consider the policy design as part of the classification and analysis. Also, Abbasabadi and Ashayeri [18] describe, characterize and compare analytics modeling approaches. Yet, the review excludes applications on energy efficiency policies. Likewise, it does not make a differentiation among building types, which limits the residential perspective.

3. Methodology

We conduct the following systematic review considering the guidelines of Kitchenham and Charters [34], Normadhi et al. [35], and Moher et al. [36]. Figure 1 shows the executed phases, and we describe them in detail in the following sections.

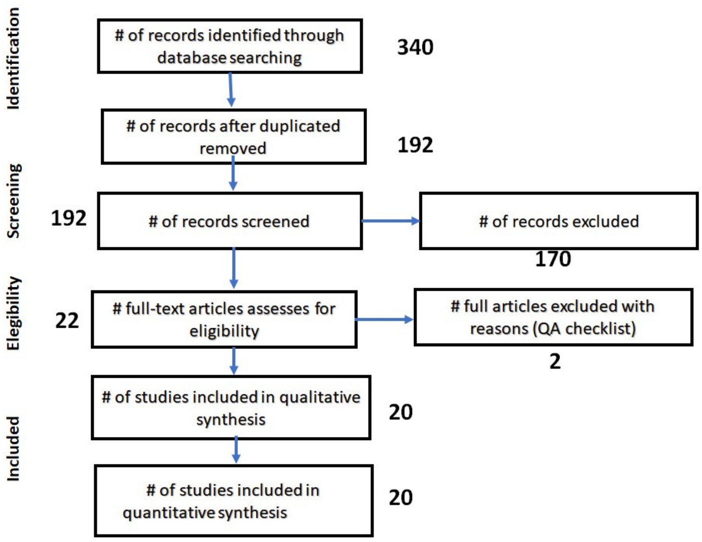

Figure 1. Systematic Review phases (adapted from [36]).

3.1. Identification Phase

We start carrying out trial searches to find systematic reviews related to our field of study. The retrieved studies guide us to discover research opportunities and establish specific research questions (RQs).

1. RQ1: What characteristics have bottom-up energy models that support energy efficiency policy design in the residential sector and residential buildings?
2. RQ2: Which analytical techniques are used in bottom-up energy models to support energy efficiency policy design in the residential sector and residential buildings?
3. RQ3: Which types of energy policies are supported by bottom-up energy models in the residential sector and residential buildings?

3.1.1. Search Strategy

We perform manual and automated searches to find studies in scientific databases (i.e., IEEExplorer, ACM, Science Direct, Google Scholar, and Scopus). Since diverse databases have restrictions in the number of keywords accepted within queries, we create programs to generate customized searches per database. Further, we use APIs to perform the query execution and article extraction processes in two of them. Although, the automation facilitates the retrieval of possible studies from databases. Yet, we use manual extraction when we do not have access to the corresponding SearchAPI.

The authors simplify the scope by identifying domains of study and related keywords. From the RQs, we select the following study domains: (1) Energy Efficiency, (2) Residential sector and residential buildings, (3) Analytics techniques, (4) Energy modeling, and (5) Policy Design.

3.1.2. Keyword Identification and Selection

In this stage, we propose an objective approach for keyword selection that relies on keywords from formal taxonomies and terms available in top journals and conferences. In contrast with the classic method, in which researchers select keywords based on expertise and domain knowledge. Our approach includes relevant keywords and excludes non-used terms in publications oriented to the research domain.

First, the selection process involves the identification of keywords for each domain of study in formal taxonomies (e.g., IEEE and ACM) and journals related to energy efficiency policy (e.g., Energy Efficiency Journal, Energy Policy, Energy and Buildings, Applied Energy and Energy Procedia). Second, using this initial list of terms, we look for synonyms present in scientific databases, using trial queries. Finally, we select the final keywords using the following criteria: (1) Keywords present in more than one publication are included in the final keyword list (2) Keywords with one or more synonyms are included in the list (e.g., data driven, data-driven) and (3) If synonyms share a similar expression(e.g., model-based, modeling, models), we use the shared term as key term (e.g., model). Table 3 shows the keywords used for query construction.

Table 3. Keywords by Domain of Study.

Domains of Study	Keywords (IEEE/ACM/Indexed Journals) and Synonyms
DS1. Energy Efficiency	Energy efficiency, energy-efficiency, CO_2, appliance, technology, energy conservation, retrofit, energy saving, insulation
DS2. Residential Sector and Residential Buildings	Household, dwelling , residential
DS3. Analytics techniques	Analytics, mining, prediction, data analysis, decision support, forecast,time series, regression, data-driven, data driven, Machine learning
DS4. Energy Modeling	Model
DS5. Policy design	Policy, policies, regulation, scenario, intervention, program, incentive

3.1.3. Query Construction

We automate the query generation using a Phyton application to obtain relevant domain-related articles. Although, the program generates a set of queries that includes all possible keyword combinations. The creation process reveals that some databases require numerous searches to obtain all potential publications. A circumstance that can result in an unmanageable number of publications to review.

To address this situation, we propose the following inclusion/exclusion criteria. So we can guarantee the creation of manageable and domain-oriented queries.

The inclusion criteria involve:

1. Queries that consider papers published after 2014 and with a compelling keyword combination in its title. We review articles from the last five years of research.

2. Queries that include the following combination of domains: DS1, DS2, and DS3 or DS1, DS2, and DS4. We exclude the policy term (DS5) since it affects the query result. For instance, using DS5 keywords, we retrieve an excessive or limited number of articles with poor orientation to the study domain. To overcome this problem, we validate the article's policy orientation in future phases.

Table 4 shows the keyword combinations used for query construction.

Table 4. Queries with their keyword combination.

Query	**Domain Combination**	**Keywords in Query**	**Constraint**
Q1	DS1, DS2 and DS3	"energy efficiency" OR energy-efficiency OR CO_2 OR appliance OR technology OR "energy conservation" OR retrofit OR "energy saving" OR insulation AND household OR dwelling OR residential AND "machine learning" OR analytics OR mining OR prediction OR "data analysis" OR "decision support" OR forecast OR "time series" OR regression OR "data-driven" OR "data driven"	TITLE AND Year $>$ 2014
Q2	DS1, DS2 and DS4	"energy efficiency" OR energy-efficiency OR CO_2 OR appliance OR technology OR "energy conservation" OR retrofit OR "energy saving" OR insulation AND household OR dwelling OR residential AND model	TITLE AND Year $>$ 2014

On the other hand, we filter the queries using the following exclusion criteria:

1. Queries that return more than 200 records and that that fail to pass a pre-screening process. In this case, we perform manual screening to validate the granularity of the returned articles. If we detect that the majority of records are not in the scope of the research, we discard them. In future examinations, we plan to automate this screening process.

After applying the inclusion/exclusion criteria, the program returns a total of 396 accepted queries. See Table 5 for the query generation summary per database.

The previous procedure permits quality assurance of the results and eases the automatic extraction of articles from databases. The query generation program is available for review in the following GitHub repository: https://github.com/tsetsuna/Systematic-Review (accessed 30 August 2021).

3.1.4. Query Execution

We automate the query execution and article retrieval for IEEE and Scopus databases using IEEE Python and ElsClient Python APIs. On the other hand, we download publications from ACM, Google Scholar, and Science Direct directly from each database portal.

The query execution summary available in Table 5 reveals a total of 340 retrieved publications. From Google Scholar and Scopus databases, we retrieve most of the articles with 118 and 112, respectively. Also, we remove 148 out of 340 publications identified as duplicated per specific database and by comparing all databases (e.g., de-duplicated). In the end, we obtain 192 unique articles after inclusion/exclusion criteria. For duplicate removal, we use the EndNote application.

Table 5. Number of articles obtained after query execution.

Database	Num. Queries	Num. Articles	Duplicated	After Duplicates	Deduplicated	Final
IEEE	312	38	8	30		
ACM	2	16	1	15		
Science Direct	56	56	3	53	105	192
Scopus	2	112	8	104		
Google Scholar	24	118	23	95		
TOTAL	396	340	43	297	105	192

3.2. Screening Phase

We use the Rayyan application which is a specialized tool to perform systematic reviews and to filter publications according to a defined inclusion and exclusion criteria. The program facilitates paper labeling and parallel revisions among reviewers. More information about Rayyan can be found in: https://rayyan.qcri.org/welcome (accessed on 30 August 2021).

To begin article screening, we export unique articles from EndNote to Rayyan and coordinate reviews among contributors. All authors participate in the screening process. Lastly, we apply inclusion and exclusion criteria to examine the articles.

The inclusion criteria involve:

1. Research papers (RPs) published between 2015 and 2020 will be considered for the study.
2. RPs that allow to answer the defined research questions
3. RPs from journals and conferences (with citations)
4. RPs should be in English
5. RPs should have an available and complete abstract

On the other hand, the exclusion criteria eliminate:

1. RPs without models applied to the residential sector or residential buildings
2. RPs without policy orientation. The abstract or title must include at least one of the following terms: policy, policies, regulation, scenario, intervention, program, or incentive.
3. RPs without orientation to energy efficiency (i.e., energy savings or energy conservation)
4. RPs without application to electricity end-use

Finally, after applying the inclusion and exclusion criteria, we accept 22 articles for quality validation and discard 170 out of 192.

3.3. Eligibility and Inclusion Phases

The quality validation of articles aims to guarantee the inclusion of studies that contain information that allows answering the RQs. We design a straightforward checklist to identify publications that are compliant with the requirements of the study. The complete QA checklist is available in Table 6.

The quality criteria CK1 aims to identify the articles' orientation concerning bottom-up energy models and energy efficiency policy. If the publication does not consider those subjects, the answer to the question is negative. Secondly, CK2 and CK4 are used to identify specific features of bottom-up energy models. In this regard, if definitions of variables/methods are not present, the answer to the criteria is negative. Lastly, Ck3 and Ck5 are used to assess how accurate the data analysis is. If no validation procedure is present, the answer to the criteria is negative. We apply the quality criteria to 22 articles.

Figure 2 shows the results of the checklist execution. The summary of findings is the following: (1) 100% of studies have a correct orientation to bottom-up energy models and energy efficiency policy (2) 95% of publications describe exogenous and endogenous variables of the energy model (only two of them don't) (3) 90% of articles describe the measuring process of the model's variables (4) 95% studies describe the methods to analyze the model's data and (5) 68% of publications present a validation procedure. In the end, two studies accomplish less than four affirmative criteria, while 20 publications achieve four or more. This last fact allows us to identify the articles to be excluded from the final analysis and consider only those who achieve compliance with at least 80% of the quality criteria. At the end, only 20 studies passed the quality check, and 2 out of 22 were rejected.

Table 6. Quality Checklist.

Item	Assessment Criteria	Checklist Description
CK1	Are the aims of the article clearly defined?	No, the aim is not defined Yes, the aim is clearly defined
CK2	Are endogenous and exogenous variables of the model described?	No, the variables are not described Yes, the variables are clearly listed and described
CK3	Are the variables used in the study adequately measured?	No, the variables measurement process is not explained or justified Yes, the variable measurement process is clearly explained and justified.
CK4	Are methods for analyzing model's data described?	No, the methods for data analysis are not described nor explained Yes, the methods for data analysis are clearly described and explained.
CK5	Do the study present a validation procedure?	No, the study does not present a validation procedure of the obtained results Yes, the study presents a validation procedure of the obtained results.

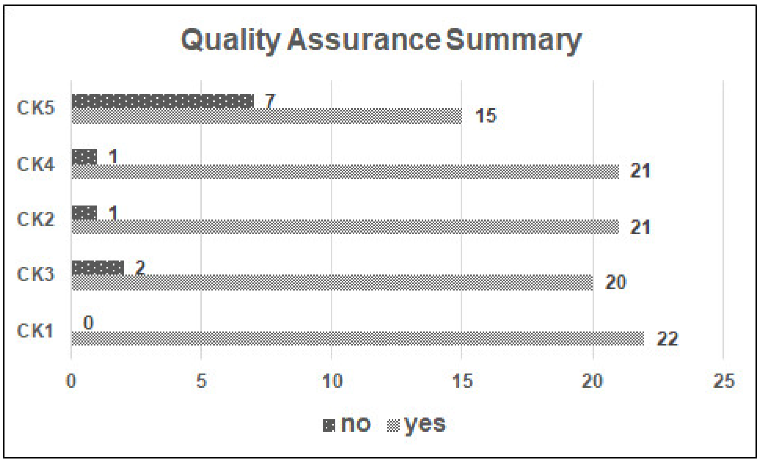

Figure 2. Quality Assurance Summary.

Ultimately, we organize research papers according to the following aspects of models. First, the taxonomy of bottom-up energy models available in Table 2 (e.g., sector coverage, geographical coverage, time horizon, methodologies, end-use energy modeling, programming techniques, data time split, metrics and tools, and residential electricity end-uses). Second, the policy instruments supported (e.g., market-based, financial, regulatory, information and feedback, and non-regulatory). And finally, the utilization of specific analytics methods available in the model.

The described organization allows the analysis of models from different facets with a quantitative and qualitative perspective. Table 7 shows a partial categorization of QA approved studies.

Table 7. Article Classification by Bottom-up model characteristics.

Citation	Authors	Consumer Sector	Sector Coverage	Geographical Coverage	Time Horizon	Methodology	Modeling Technique	Programming Technique	Electricity End-Use	Technique Used
[37]	Jridi et al.	Residential	Single-Sectorial	Local	Short	Economic	DDS	Other	AL	Discrete choice models (Logit model)
[38]	Hara et al.	Residential	Single-Sectorial	Local	Medium	Economic	DDS	Other	SC	Discrete choice models (Logit and probit), Time-series analysis
[39]	Marshall et al.	Building	Single-Sectorial	Local	Short	Simulation	E	Other	SH	Transient Thermodynamics equations
[40]	Braulio Gonzalo et al.	Building	Single-Sectorial	Local	Short	Simulation	E	Other	SH, SC	Bayesian Inference, INLA (Integrated Nested Laplace Approximation)
[41]	M. Aghamohamadi et al.	Residential	Single-Sectorial	Local	Short	Optimization	DDS	Other	AL, SC	Probability Density Functions Least Square Method, Person distribution
[42]	w. Kleebrang et al.	Residential	Multi-Sectorial	Local	Long-Term	Economic	DDS	Other	AL, SC, WH	End-use Model Linear Regression
[43]	A. Mohseni et al.	Residential	Single-Sectorial	Project	Short	Optimization	DDS	Mixed LP	A, SC	Set of Sequential Uninterruptible Energy Phases MILP
[44]	Schutz et al.	Building	Single-Sectorial	Project	Short	Optimization	E	Mixed LP	SH, SC	Dynamic Building Model MILP
[45]	Radpour et al.	Residential	Single-Sectorial	Local	Long-Term	Economic	DDS	Other	A	Econometric diffusion models, market share functions energy system parameters
[46]	Cerezo Davila et al.	Building	Single-Sectorial	Local	Long-Term	Simulation	E	Other	AL, SC	Occupant uncertainty modeling
[47]	Jafary et al.	Residential	Single-Sectorial	Project	Short	Other	DDS, DDAI	Other	A	Cluster analysis Regression analysis
[48]	Heidari et al.	Residential	Single-Sectorial	Local	Long-Term	Economic	DDS	Other	L	Material flow analysis (MFA) Weibull distribution, Techno-economic analysis
[49]	Pradhan et al.	Residential	Multi-Sectorial	National	Long-Term	Optimization	DDS	Linear Programming	C	Linear optimization
[50]	Lundgren et al.	Residential	Single-Sectorial	Local	Medium	Other	DDS, DDAI	Other	AL	Two level time series mediation model, Regression analysis, Principal Component analysis
[51]	Meangbua et al.	Residential	Single-Sectorial	Local	Medium	Other	DDS	Other	SC	Panel data regression
[52]	Wang et al.	Building	Single-Sectorial	Local	Short	Other	DDS	Other	SC, SH	Propensity score matching method
[53]	Wen and Cao	Residential	Single-Sectorial	Local	Medium	Other	DDS, DDAI	Heuristic	SC, A	Bivariate correlation analysis Butterfly optimization algorithm, Least square support vector machine
[54]	Liang et al.	Residential	Single-Sectorial	Project	Short	Other	DDS	Other	A	Sliding Window Linear Regression, Kernel Density
[55]	Wen and Cao	Residential	Single-Sectorial	Local	Long-Term	Other	DDS, DDAI	Heuristic	SC, A	Grey Relational analysis, chicken swarm optimization, Support Vector Machine
[56]	Krarti et al.	Building	Single-Sectorial	Local	Long-Term	Simulation	E	Other	AL, SC	Mathematical equations

Note: Electricity end-uses: AL = Appliances and Lighting, SC = Space Cooling, SH = Space Heating, WH = Water Heating, A = Appliances, L = Lighting, C = Cooking. Modeling Techniques: DDAI = Data-driven AI-Based, DDS = Data-driven statistical, E = Engineering.

4. Results and Discussion

We contemplate approved QA papers (i.e., 20 articles) to perform quantitative analysis and respond to the defined research questions.

4.1. Summary of Selected Studies

Figure 3 shows the distribution per year of studies. As can be noticed, the quantity of papers focused on bottom-up energy models that support energy efficiency policy design is low, with an average of three publications per year. However, this number can increase to some extent if we consider that 2020 publications were obtained from January to June 2020, excluding the last two quarters of the year.

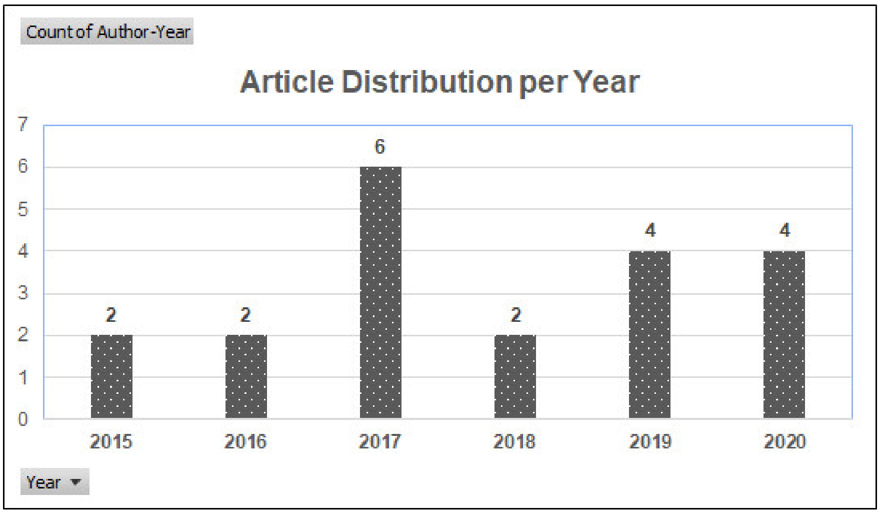

Figure 3. Distribution graph of the number of articles per year.

4.2. Analysis by Consumer Sector

We performed the articles' analysis by sector (e.g., residential sector and residential buildings) to discover the characteristics of bottom-up energy models and the policy orientation of each of them.

Figure 4 shows how the residential sector surpasses by more than double the number of residential buildings publications. The last statistic is coherent; if we consider that energy policy modeling for buildings is a new field of study, in contrast to the residential sector, which has documented research since the 70 s [57].

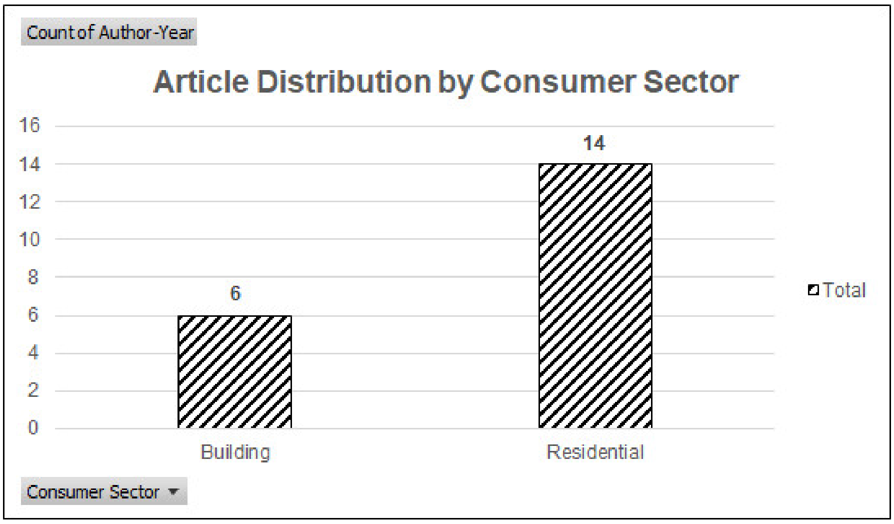

Figure 4. Distribution graph of number of articles by Consumer Sector.

4.3. Results

In this section, we answer the defined RQs.

RQ1: What kind of bottom-up energy models aim to support policy design of electricity end-use efficiency for residential buildings and the residential sector, and how do they relate to specific policy instruments

The following features are selected to characterize bottom-up energy models that support policy design of electricity end-use efficiency: sector and geographical coverage and time horizon, obtained from the taxonomy in Table 2. Likewise, we incorporate the electricity end-use, data time split, cost and CO_2 emissions included within the model, and the use of scenarios. The characteristics of bottom-up energy models for the residential sector are available in Table 8 and for residential buildings in Table 9.

Table 8. Characteristics of bottom-up energy models-Residential Sector.

Citation	Authors	Sector Coverage	Geographic Coverage	Time Horizon	Electricity End-Uses	Data	Cost	Scenario Based	CO_2
[37]	Jridi et al.	Single-sector	Local	Short	AL	Yearly	no	no	no
[41]	Aghamohamadi and Amjady				A, L, SC	Hourly	yes	yes	no
[38]	Hara et al.	Single-sector	Local	Medium	SC	Yearly	no	no	no
[50]	Lundgren and Schultzberg				AL	Yearly	yes	no	no
[51]	Meangbua et al.				SC	Yearly	no	no	yes
[53]	Wen and Cao				A, SC	Yearly	no	no	yes
[45]	Radpour et al.	Single-sector	Local	Long-term	A	Yearly	yes	yes	no
[48]	Heidari et al.				L	Yearly	yes	yes	no
[55]	Wen and Cao				A, SC	Yearly	no	no	yes
[43]	A. Mohseni et al.	Single-sector	Project	Short	A, SC	Hourly	yes	yes	no
[47]	Jafary and Shephard				A	Hourly	no	no	no
[54]	Liang et al.				A	Hourly	no	yes	no
[42]	w. Kleebrang et al.	Multi-sector	Local	Long-term	A, L, SC, WH	Yearly	no	yes	no
[49]	Pradhan et al.	Multi-sector	National	Long-term	C	Yearly	yes	yes	yes

Note: Electricity end-uses: AL = Appliances and Lighting, SC = Space Cooling, SH = Space Heating, WH = Water Heating, A = Appliances, L = Lighting, C = Cooking.

Residential Sector

Bottom-up energy models for households are single-sector models with local coverage and different time horizons (e.g., short, medium, or long-term). Evidence shows that most of these models (i.e., 71%) depend on surveys and statistical data for model construction and have a yearly data time split. The only exception is Aghamohamadi & Amjady's model [41], which uses a sampling of appliance energy consumption with hourly resolution. Likewise, the models have the following applications: behavioral studies towards energy efficiency, perception of electricity consumption, determinant factors of appliance replacement, CO_2 energy requirements, appliances and bulbs replacement, appliances market penetration, and emissions in electricity production. Therefore, we can conclude that they aim to address failures on consumer behavior of end-users and on access to capital measures in the case of appliance replacement [6], which makes them useful for financial and regulatory instruments design. However, their limited geographical coverage does not allow their applicability for regional or international policy design.

In contrast, single-sector bottom-up energy models with project coverage are short time horizon models that rely on granular time split with minute resolution. Two studies use the Pecan Street dataset to analyze household baseload consumption [54] and model appliances benchmark [47]. Likewise, Mohseni et al. [43] use smart meter samples to create an energy model for day-ahead planning. Given the short time horizon and data time split, we deduce that these models deal with imperfect information barriers among consumers and energy suppliers [6], which allows us to correlate them with information and feedback policy instruments.

Also, we identify a limited set of multi-sector models in the literature. Yet, they characterize as long-time horizon models with yearly data time split. For instance, Kleebrang et al. [42] create a long-term model (2013–2030) for lighting and air conditioning replacement in Vientiane, Lao PDR, taking into account the residential and the economic sectors. Likewise, Pradhan et al. [49] analyze the effects of electricity-based and bio-gas cooking from 2010 to 2050 in Nepal considering the same two sectors. These models can address the problem of markets that undersupply services like energy efficiency [6]. For instance, governments at the national or regional level can apply regulatory instruments to guarantee a minimum energy efficiency level in products or services.

On the other hand, in terms of energy end-uses, 50% of studies include Appliances (A) end-use in their models, 50% Space Cooling (SC) (i.e., air conditioning), and 35% Lighting (L). Unique studies include Water Heating (WH) and Cooking (C) end-uses. Aghamohamadi and Amjady [41] report the larger number of end-uses included in a single-sector model by incorporating three end-uses (e.g., A, L and SC). Likewise, Kleebrang et al. [42] are the multi-sector leaders by comprising four end-uses within a model (e.g., A, L, SC, WH).

Additionally, the use of scenarios is present in 50% of bottom-up energy models for the residential sector. Multi-sector bottom-up energy models report the highest utilization of scenarios with 100% and the least in single-sector models with local coverage and medium time horizon with 0%. Likewise, 50% of studies provide results using: CO_2 emissions (28%) or cost (42%). The article that includes all three characteristics (e.g., scenarios, CO_2 emissions, and cost) is documented by Pradhan et al. [49] in 2017; however, the model is useful exclusively for the cooking end-use. These statistics reveal concerns if we compare these models with a model-based decision support system. Since this last should include the following components to guarantee decision support [58]: (1) a user interface (e.g., scenarios) and organizing module (2) a database (3) a model base (e.g., variables and metrics) and (4) and algorithmic base or library (e.g., analytical methods portfolio). Therefore, based on this definition, we can affirm that only 50% of the analyzed studies create decision/policy support models.

Residential Buildings

Differently, for residential buildings, bottom-up energy models reveal to be single-sector, local, or project in their geographical coverage with short or long-term time-horizons. In contrast to the residential sector, these models include the following proportion of energy end-uses: SH (66%), SC (83%), and some articles include appliance or lighting end-uses (33%). Besides, 50% of the studies provide cost information in their results, and the same percentage use scenarios to present results. Schtz et al.'s model [44] is the only study that provides the CO_2 metric. The described features indicate that these models are not focused to support national or regional policy decisions but local regulations. Likewise, their support to policy design is also limited as in the households case.

Evidence shows that bottom-up energy models for residential buildings depends on information from literature, surveys, statistics, and simulated data to model creation. The data time split of this kind of model in its majority has a yearly resolution (i.e., 50%) and in less proportion (i.e., 16%), monthly, daily, and hourly.

Finally, we find the following applications in these models: energy saving scenarios, energy performance assessment, building energy standards validation, retrofit scenarios, and optimization of energy systems and envelops.

Table 9. Characteristics of bottom-up energy models—Residential Buildings.

Citation	Authors	Sector Coverage	Geographic Coverage	Time Horizon	Electricity End-Uses	Data	Cost	Scenario Based	CO_2
[39]	Marshall et al.	Single-sector	Local	Short	SH	Yearly	no	yes	no
[40]	Braulio Gonzalo et al.				SH, SC	Daily	no	no	no
[52]	Wang et al.				SH, SC	Monthly	no	no	no
[46]	Davila et al.	Single-sector	Local	Long-term	A, L, SC	Yearly	yes	yes	no
[56]	Krarti et al.				A, L, SC	Yearly	yes	no	no
[44]	Schutz et al.	Single-sector	Project	Short	SH, SC	Hourly	yes	yes	yes

Note: Electricity end-uses: AL = Appliances and Lighting, SC = Space Cooling, SH = Space Heating, WH = Water Heating, A = Appliances, L = Lighting, C = Cooking.

RQ2: Which types of analytical methods are used in bottom-up energy models that aim to support policy design of electricity end-use efficiency in residential buildings and the residential sector?

The distribution of studies, according to the modeling technique, can be visualized in Figure 5. As stated in the graph, most models (55%) use a data-driven statistical modeling technique in their development. Followed by: data-driven hybrid techniques (e.g., data-driven statistical+AI-based) with 20%, engineering modeling techniques with 15%, and engineering-statistical hybrid techniques (e.g., engineering+data-driven statistical) with 10%. A detailed summary of modeling techniques and methodologies used in both sectors is available in Tables 10 and 11 respectively.

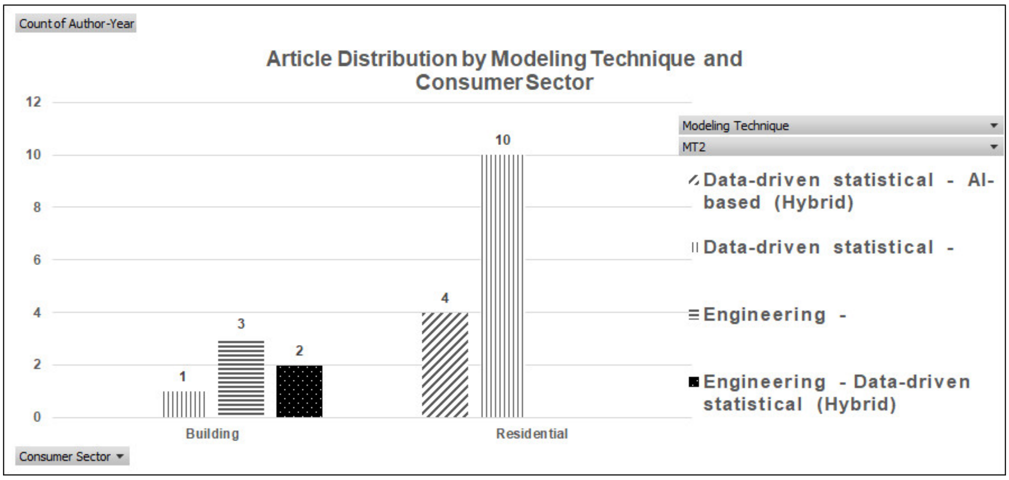

Figure 5. Distribution graph of number of articles by Modeling Technique.

Residential Sector

For the residential sector, we identify two central energy modeling techniques applied: data-driven statistical (DDS) with 72% and data-driven hybrid (DDH) techniques(e.g., statistical+AI-based) with 28%. The results reveal the utilization of DDS modeling with economic, optimization, or miscellaneous methodologies. We also identify that the economic approach is the most commonly used in this kind of study (50% of the articles), followed by optimization (30%) and other non-categorized methods (20%). See Figure 6. Differently, only non-categorized (i.e., other) methodologies are used in DDH modeling techniques. See Table 10 for a complete list of techniques and methodologies used in the residential sector.

Table 10. Techniques and Methodologies used in bottom-up energy models that support energy efficiency policy design—Residential Sector.

Modeling Technique	Methodology	Programming Technique	Techniques Used	Citations
Data-driven statistical	Economic	Other	Discrete choice models (Logit model or/and probit models), time-series analysis, end-use model, linear Regression, econometric diffusion models, market share functions, material flow analysis (MFA), weibull distribution, techno-economic analysis	[37,38,42,45,48]
	Optimization	Other	Probability Density Functions, least Square Method, Pearson distribution	[41]
		Linear Programming	Linear optimization	[49]
		Mixed LP	Set of sequential uninterruptible energy phases, MILP	[43]
	Other	Other	Panel data regression, Sliding window linear regression, kernel density	[51,54]
Data-driven statistical and data-driven AI-based (Hybrid)	Other	Other	Cluster analysis, regression analysis, two level time series, mediation model, regression analysis, principal component analysis	[47,50]
		Heuristic	Bivariate correlation analysis, Butterfly optimization algorithm, Least square support vector machine, Grey relational analysis, Chicken swarm optimization, Support Vector Machine	[53,55]

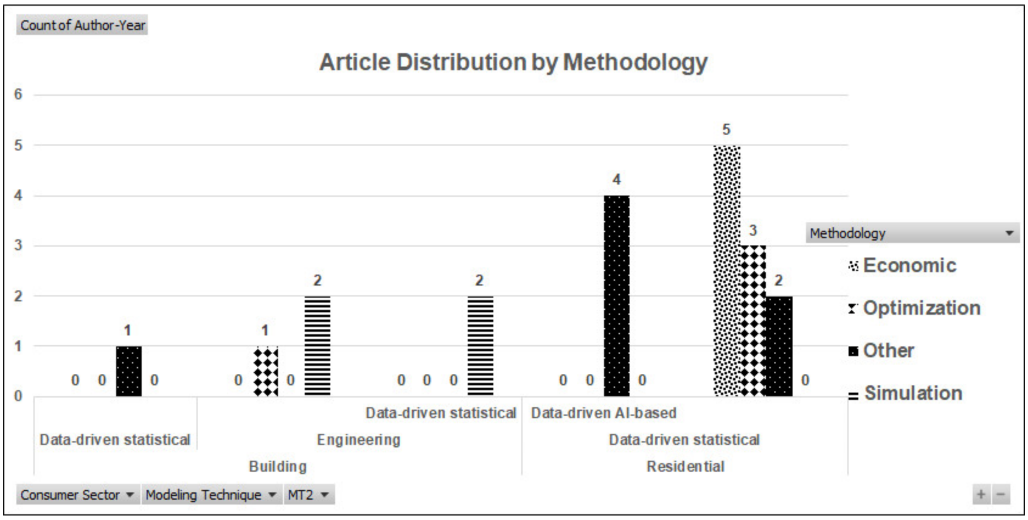

Figure 6. Distribution graph of number of articles by Methodology.

Economic DDS Models

The literature reveals that economic DDS models focus on appliances and utilize econometric modeling techniques. For instance, Jridi et al. [37] study factors that influence the adoption of water heaters, efficient refrigerators, and energy-saving bulbs using discrete choice models. Likewise, Hara et al. in [38] use the same technique, but to analyze electricity end-use consumption. On the other hand, Radpour et al. [45] create a long-term penetration model of energy-efficient appliances using econometric diffusion modeling that considers refrigerators, freezers, dishwashers, clothes washers, clothes dryers, and ranges. Kleebrang et al. [42] design a long-term model to predict household electricity demand

and energy-saving potential by appliance replacement in Vientianne using regression and scenario analyses. Finally, lighting end-use is studied by Heidari et al. [48] using Material Flow Analysis and considering: legislation and evolution of lighting technology.

As can be regarded, these models focus on analyzing scenarios of technology replacement, which can support the implementation of regulatory and financial instruments.

Optimization DDS Models

The revised optimization models use statistical techniques to analyze energy end-use features and optimize energy investment choices. In this systematic review, we find out that most optimization models in this category focus on appliance modeling. For instance, in [43] , Mohseni et al. describe the modeling of appliances energy consumption in a residential microgrid to create a day-ahead energy management framework and support time-based demand response programs. The authors use SSUEP (i.e., Set of Sequential Uninterruptible Energy Phases) and MILP optimization framework to identify optimal time-based scenarios of energy consumption for different appliances in combination with photovoltaic(PV) systems, battery energy storages, and electric vehicles. The study reveals that diminishing peak power and energy cost in the microgrid is possible. Similarly, Aghamohamadi and Amjady [41] presents an analytical tool to optimize households' energy efficiency programs using probability distributions and the least square method. The study focuses on providing the most cost-effective solution to specific end-users based on their income level. The authors report an expected increase in energy savings and a decrease in energy cost. Finally, Pradhan et al. [49] create a long-term model using linear optimization techniques to adjust Nepal's energy mix considering cleaner energy sources in the residential sector. The introduction of electric and bio-gas based cooking devices is analyzed using four scenarios that measure: total primary energy supply (toe), fuel use in the residential sector (toe), electricity generation requirements (TWh), and GHG emissions in the residential sector.

Finally, the results of these models can be relevant in the design of market-based and non-regulatory instruments, given the possibility to adjust energy prices and diminish greenhouse emissions by energy suppliers.

DDS Models with Other Methodologies

The identified DSS models with non-categorized methodologies appear to be exploratory and descriptive. For instance, Meangbua et al. [51] perform a model to determine factors of households' energy and CO_2 requirements, using panel data regression. The authors discover influencing factors on energy and CO_2 requirements in Thailand (e.g., temperature and education). The study concludes that change on factors depends on the country and its specific-energy policy. On the other hand, Liang et al. [54] create a model to evaluate domestic appliances' constant power (i.e., baseload). Sliding Window Linear Regression is used to find consistent power-consuming segments and Kernel Density to improve baseload discovery accuracy. The model's input contemplates data from smart meters and daily temperature, while average baseload power, baseload temperature sensitivity, and energy-saving potential as final outputs.

The first study can be used to define information and feedback instruments that improve people's education. In the second, the energy supplier can provide subsidies and promote appliance replacement to decrease energy consumption.

DDH Models with Other Methodologies

Hybrid models use statistical and artificial intelligence techniques to analyze energy end-use features. One common characteristic of these models is the utilization of non-categorized methodologies, as shown in the following publications. In [50], Lundgren and Schultzberg design a model to understand the behavior towards energy-efficiency in households using regression analysis, time series mediation model, and principal component analysis. This model analyses behavior considering: the sensitivity to electricity price, the monitoring habits like supervise energy bills and energy meters, cutting activities like turn off appliances or leave them on, and upgrading actions like the acquisition of energy-efficient products or replacement of non-efficient ones. The authors conclude that levels of energy efficiency behavior do not impact the level of electricity consumption.

From another perspective, Jafary and Shepard [47] perform an analysis to identify factors that affect appliance energy consumption variability in a sustainably designed community. Energy consumption is analyzed using clustering and regression analysis, considering building attributes (BAs) and socio-econo-mic characteristics (SECs). The study concludes that BAs, SECs, and occupant behavior influence the energy consumption of appliances. Likewise, Wen and Cao, in the following papers [53,55], present two predictive models to analyze CO_2 emissions and their influence factors in the residential sector. The authors use an innovative combination of techniques (e.g., bi-variate correlation analysis, kernel principal component analysis, butterfly optimization algorithm, and least square support vector machine) to perform the CO_2 emissions prediction. The study compares the prediction accuracy of six models versus the actual emission metrics.

As can be regarded, these hybrid models concentrate on user behavior, which can be beneficial for information and feedback instruments' design.

Residential Buildings

For residential buildings, the majority of studies (50%) use engineering modeling techniques, followed by data-driven statistical (DDS) with 25% and a hybrid combination of engineering and DDS techniques (EDDS) with also 25%. See Figure 5. The majority of residential building studies (66%) use simulation in model development, followed by optimization and non-categorized methodologies with 17%. See Figure 6. Finally, regarding programming techniques, 75% of publications use non-categori-zed techniques, followed by Mixed LP with 25%. As in the residential sector, we include a complete list of techniques used in the building sector in Table 11. Also, we provide a detailed description of the studies in this section.

Table 11. Techniques and Methodologies used in bottom-up energy models that support energy efficiency policy design—Residential Buildings.

Modeling Technique	Methodology	Programming Technique	Techniques used	Citations
Data-driven statistical	Other	Other	Propensity score matching method	[52]
Engineering	Simulation	Other	Transient thermodynamics equations, mathematical equations	[39,56]
	Optimization	Mixed LP	Dynamic Building Model, MILP	[44]
Engineering-Data-driven statistical (Hybrid)	Simulation	Other	Occupant uncertainty modeling, Bayesian inference, INLA (Integrated Nested Laplace Approximation)	[40,46]

Engineering Models with Simulation

This kind of bottom-up energy models calculates energy consumption based on thermodynamics and heat transfer of end-uses to replicate the energy system operation. We identify the following publications as part of this category: In [39], Marshall et al. implement a model that allows the visualization of energy-saving scenarios in residential buildings by the application of Energy Efficiency Measures. The authors use transient thermodynamic equations to calculate annual savings of heating demand in a building. The model considers the application of one or more of the following energy efficiency measures types: conversion of devices (e.g., boiler upgrade), passive system (e.g., solid wall and roof insulation), service control (e.g., use of thermostatic radiator and zonal heat controls) and service level (e.g., reducing internal temperature and partial heating house). Yet, the model does not include non-summer cooling demand and other types of house archetypes, climates, or occupancy patterns (e.g., the elderly). Additionally, Krarti et al. [56] design a model to evaluate residential buildings' energy efficiency programs. Different from the previous model, this one uses 54 archetypes and simulations to calculate energy consumption. The model includes the following building retrofit strategies in the stock model: envelope components, appliances, air conditioning systems, occupancy behavior changes, and cool roofs. The authors discover that a target and complete implementation of retrofit programs can reduce by 50% the annual energy consumption in the king of Saudi Arabia.

Finally, these models are valuable to support technology replacement and support regulatory instruments.

Engineering Models with Optimization

Engineering models that use optimization methodologies calculate energy consumption based on thermodynamics and heat transfer of end-uses to optimize energy investment choices (e.g., financial and/or regulatory instruments). We identify the following research paper as part of this category in the literature: In [44], Schütz et al. present a building model useful for assessing the building's dynamic behavior considering the energy system optimization and its envelope. The model allows the evaluation of retrofitting options (e.g., PV unit installation and envelop modernization) by calculating the cost of technology adoption and total CO_2 emissions. The authors conclude that the model is compliant with approved building standards and assesses buildings' dynamics behavior (e.g., indoor air temperature and annual heat loads). However, the model has a drawback; it includes a limited stock of heating devices, affecting its applicability in other environments.

EDDS Hybrid Models with Simulation

EDDS hybrid models are used to calculate energy consumption based on thermodynamics, heat transfer, and supported by statistical techniques to replicate the energy system operation. For this category, we find the following research papers. Braulio-Gonzalo et al. [40] model the passive energy efficiency performance of a residential building stock using Bayesian inference. A set of forecasting models with different co-variants is assessed by how well they fit the data. As a result, the authors reveal the key parameters of buildings performance. Even though the model calculates building stocks' performance at an urban scale, it excludes possible important co-variants like energy demand or discomfort hours. A second bottom-up energy model applied to urban buildings is designed by Cerezo Davila et al. [46] using building archetypes and simulation. The authors create basic and stochastic building archetypes to generate scenarios of retrofitting strategies, including its affordability and economic feasibility. The model provides two aggregation levels: neighborhood demand and single building savings, to predict energy use and cost savings. Moreover, the design includes combinations of energy efficiency strategies like equipment upgrade and building envelop retrofit, which is not common in energy efficiency modeling.

Finally, these scenarios are valuable for regulatory and financial instruments' design.

DDS Models with Other Methodologies

In this kind of bottom-up energy models, authors analyze energy end-uses using statistical techniques and non-categorized methodologies. For instance, Wang et al. [52] create a model to explore the effect of energy efficiency standards (e.g., regulatory instruments) in residential buildings using the propensity score matching method. A comparison of standard performances in buildings is provided by the model considering: appliances, occupant behavior, and building and household characteristics. The authors report a gap between the building's calculated design performance savings and its actual operation savings.

Finally, we identify a limited classification of programming techniques in both sectors. Furthermore, the utilization of methodologies like spreadsheet, back-casting, or multi-criteria is absent.

RQ3: Which types of energy policies are supported by bottom-up energy models that aim to support policy design of electricity end-use efficiency in residential buildings and the residential sector?

The distribution of policy instruments that are supported by bottom-up energy models can be visualized in Figure 7. As can be regarded, the majority of bottom-up energy models (45%) are useful to support information and feedback instruments. Followed by bottom-up energy models that support market-based and financial instruments (40%) and finally, the ones that support regulatory instruments (35%).

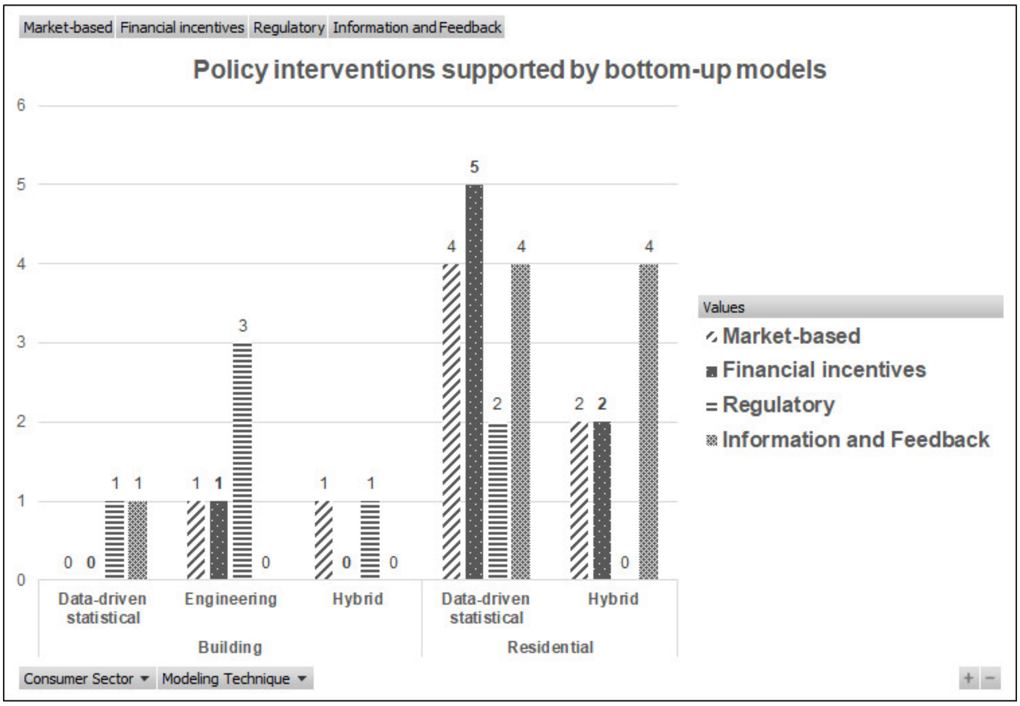

Figure 7. Distribution policy instruments supported by bottom-up models.

Residential Sector

In this sector, bottom-up energy models show the following trend regarding its capability to support policy design: information and feedback instruments are supported in 57% of the studies, followed by financial incentives with 50%, market-based with 47%, and regulatory measures with 14%. In the following sections, we describe how bottom-up energy models support policy design using diverse instruments.

Information and Feedback (IF)

Evidence shows that bottom-up energy models in the residential sector support energy policy using information and feedback policy instruments. For instance, Hara et al. [38] perform an analysis of electricity and gas-saving, revealing households' capability to reduce energy consumption. Using the model's results, the authors propose general IF instruments. However, their model does not allow simulation of specific policy instruments to support energy conservation programs. On the other hand, Mohseni et al. [43] present a model to support the planning of energy loads in a residential microgrid to diminish peak power and energy costs. The authors affirm that residential customers must be involved in the demand response strategy; however, they do not recommend specific programs to achieve that goal. In this regard, we identify that baseload profiles are useful IF instruments to include clients in energy-saving programs. A third example is a research presented by Meangbua et al. [51], where the authors analyze factors that influence energy requirements and CO_2 emissions of Thai households. The study's findings reveal that education is the key driving force to avoid barriers like the rebound effect or inadequate ideas about energy conservation methods (e.g., applying IF instruments). A final model developed by Jafary and Shepard [47] identifies determinants of appliance electricity consumption. The study reveals that education is correlated with decreasing appliance electricity consumption. However, the authors do not propose specific IF strategies.

Financial Incentives

The following models are identified to support the design of financial incentives. For example, Pradhan et al. [49] design a bottom-up energy model to evaluate different cooking technologies and their impact on energy generation. The model reveals the need to implement financial incentives to promote the acquisition of new cooking devices (e.g., access to capital measures); however, the authors do not propose it. On the other hand, the study of Liang et al. [54] analyzes the baseload power of households to create target energy efficiency programs. Based on the model's results, the authors recommend the implementation of subsidies to replace non-EE devices.

Market-Based

Radpour et al. [45] analyze the impact of incentives in the market penetration of energy-efficient appliances in Alberta, Canada. The evaluation of tax credits reveals that the effect of incentives varies among energy efficiency appliances. For instance, dishwashers and clothes washers present the highest energy efficiency penetration rate considering diverse tax credit combinations. Besides, the authors discuss the positive effect of increasing electricity price (e.g., market-based intervention) to promote the acquisition of energy efficiency appliances.

Hybrid Instruments

bottom-up energy models are also useful to support combination of policy instruments. For instance, regarding energy efficiency programs, the model of Jridi et al. [37] analyzes the effect of appliance certification programs, subsidies, and appliance prices. The authors discover that households can accept regulatory programs and that subsidies seem to be more attractive for households than low appliance prices. Although this model helps guide policy-makers in implementing subsidies, energy taxes, and codes and standards, it requires to be interpreted by an expert since it is not intuitive. In a second study, Kleebrang et al. [42] use scenarios to present the result of retrofitting programs, considering the utilization of energy efficiency devices (e.g., regulatory measures). The model reveals that policy-makers should promote labeling programs (i.e., information instruments) to incentive energy-efficiency attitudes. Also, they should use the energy-saving potential of appliance retrofit for policy design. In this model, market-based interventions like energy taxation (e.g., change in electricity price) are not considered. In a third study, Heidari et al. [48] present useful scenarios to visualize and compare the cost and energy savings of specific bulb replacement programs. Thus, it is possible to choose the most cost-effective retrofit option. Using the model's information is possible to evaluate strategies that promote efficient bulbs' penetration in households. Likewise, the study evaluates the application of discount rates provided by utility companies considering bulbs prices. The authors conclude that the replacement of specific bulbs has fewer payback time than others. A fourth model created by Aghamohamadi and Amjady [41] allows the evaluation of appliance replacement programs to optimize investment costs and energy prices. The model's results support policy decisions regarding financial incentives (e.g., access to capital measures) to be applied to certain income levels or market-based instruments (e.g., adjusting hourly electricity price).

On the other hand, Lundgren and Schultzberg's [50] model allows understanding energy efficiency behavior in households that use smart meters. Based on the study results, the authors conclude that energy-saving behavior depends on the household's belief that it is energy-efficient and on its price-sensitiveness before the intervention. The authors recommend introducing a pre-paid electricity scheme to promote rationed energy consumption and energy use monitoring (i.e., feedback interventions). Likewise, the concept of solar panel lease is introduced to eliminate investment barriers in acquiring energy efficiency devices. Finally, Wen and Cao [55] predict CO_2 emissions and their factor in the residential sector. The authors recommend making tax-free energy vehicles, subside energy efficient devices (e.g., air conditioners, solar water heaters, and electric cars), and educate people to have environmental consciousness. A similar study by Wen and Cao [53] predicts residential CO_2 emissions in a China region. In this case, the authors propose applying purchase subsidies to promote the acquisition of energy efficiency appliances, stimulation of research on energy efficiency appliances, and enhancement in the understanding of carbon reduction needs.

Residential Buildings

For residential buildings, bottom-up energy models capability to support policy design present the following tendency: regulatory instruments are supported in 83% of the studies, followed by market-based incentives with 33%, financial incentives with 17%, and finally information and feedback initiatives with 17%. In the following sections, we describe how bottom-up energy models support policy design using diverse instruments.

Regulatory Measures

In this category, we identified three studies that focus exclusively on regulatory measures. For instance, Marshall et al. [39] document a model that supports the evaluation of regulatory initiatives in residential buildings considering different occupancy patterns. The authors conclude that a combination of measures should be analyzed since there are less expensive and less intrusive options that can be discovered. A similar study is performed by Schütz et al. [44], where the authors analyze possible retrofit options. The study reveals that unconstrained retrofit (i.e., without government restrictions) can provide greater CO_2 reduction compared to building envelop improvement, given the considerable investment to perform envelop retrofits. Finally, Braulio-Gonzalo et al. [40] develop a model to evaluate the energy performance of residential building stocks. Compared to the previous studies, the model permits the identification of urban areas that require urgent interventions. Yet, the model lacks scenario-based orientation, which could difficult the evaluation of diverse policies.

Financial Incentives

Cerezo-Davila et al. [46] calculate energy potential and cost energy savings of retrofit initiatives. The model is useful for emission reduction planning and policy implementation considering energy prices and initiatives; however, it does not consider demographic, economic, or social aspects; complicating policy design for specific target groups.

Hybrid Interventions

Wang et al. [52] evaluate building energy efficiency standards in China. The study reveals that the building design performance differs from the actual energy-saving operation. The authors recommend implementing outcome-based compliance with current standards and creating energy consumption databases to support policy design. Finally, the model of Krarti et al. [56] allows evaluation of retrofit programs. The study reveals that the implementation of large scale retrofit programs can generate economic, environmental, and social advantages.

Finally, evidence reveals that residential building models (i.e., hybrid and engineering) do not support information and feedback instruments. On the other hand, for the residential sector hybrid models have not documented support for regulatory instruments. In the end, we can observe a limited policy orientation in residential buildings' data-driven statistical and hybrid models requiring attention from researchers.

5. Comparison with Other Studies and Findings

This research expands the vision regarding bottom-up energy models by creating a formal categorization of models, techniques, methodologies, energy policies, and energy end-uses applicable to the residential sector and residential buildings. Our study, in comparison to other reviews [18,19,59], presents a quantitative analysis of bottom-up energy models and policy instruments, which provides valuable insight into implementation techniques, methodologies, and metrics of models for the design of these kinds of bottom-up energy models. In this regard, we have not found a review that includes such quantitative examination and exhaustive characterization of models. For instance, Oladokun and Odesola [59] only present a critical revision of models focused on energy consumption and carbon emissions; however, the models are not analyzed by specific features, as we perform in this study. On the other hand, Mundaca and Neij [3] present a classification of energy-economic models without considering diverse methodologies or end-use modeling techniques. Differently, our study is valuable for the residential sector and residential buildings, which is missing in the literature. On this subject, Swan and Ugursal [19], Oladokun and Odesola [59], and Mundaca and Neij [3] models focus only on the residential sector. While Abbasabadi and Ashayeri [18] and Hong et al. focus their research only on building energy models. Finally, we present a comparison of models using a formal taxonomy, which has not been performed in other reviews.

5.1. Findings in RQ1

In this analysis, we realize that bottom-up energy models contribute to the support of policy design of electricity end-use efficiency by (1) implementing different techniques and methodologies that allow the representation of energy-efficiency scenarios for diverse electricity end-uses (2) allowing the configuration of scenarios (3) Permitting the representation of different objectives (e.g., diminish cost or energy consumption, change behavior towards, maximize investment, etc.). Nevertheless, we also reveal that 50% of these models partially support policy design given the absence of scenarios in models. In the same way, we expose that the limitations in the utilization of relevant metrics can also constraint their support to policy design.

On the other hand, we identify the following issues in the implemented models (1) the geographical coverage of the models is limited to be local or project (2) bottom-up energy models include a limited set of electricity end-uses, restricting their capability to represent complete energy systems for the residential sector and residential buildings (3) The sector coverage is limited to single-sector models (4) the design of models with hourly/minute, daily, or week resolutions still scarce.

5.2. Findings in RQ2

The research allows identifying all kinds of techniques used in the design of bottom-up energy models. The results reveal that the residential sector relies on data-driven energy models, while residential buildings depend on engineering models. However, the studies show a disconnection between the analytics techniques, the model base, and the user interface (e.g., scenarios). Likewise, we also realize that these models do not provide a portfolio of analytical methods which constrain their capability to support the design of policies.

On the other hand, the study reveals a trend in adopting hybrid methodologies in both consumption sectors. We can explain this by considering the current availability of information from diverse sources (e.g., smart meters, surveys, databases, etc.), which was not available in the past for these kinds of studies.

Finally, in this analysis, we observe that most articles rely on non-categorized methodologies. This last implies that the literature's taxonomy does not reflect newly utilized methods and their classification. Something similar occurs with the programming technique since its taxonomy is oriented mainly on techniques used in the optimization methodology. The limitations of the current categorization should be examined in future research.

5.3. Findings in RQ3

The analysis reveals that bottom-up energy models for the residential sector provide information to support market-based, financial, regulatory, and information-feedback interventions. However, for residential buildings this tendency is not clear, since these models have limitations to support diverse instruments. Besides, we recognize that bottom-up energy models do not support non-regulatory interventions, which presents a research opportunity in this field.

Additionally, we understand that the design of bottom-up energy models focuses on representing specific policy scenarios but not on implementing diverse policy instruments. This last has created an issue in the development of bottom-up energy models since modelers built customized scenarios of energy systems; however, they do not characterize and represent diverse policy instruments and how they affect the energy system. This finding is present in all analyzed articles.

Finally, we learn that bottom-up energy models design does not include an intuitive user interface that eases model interaction and scenario analysis to policy-makers.

6. Conclusions and Future Work

This systematic review provides a multi-facet perspective of bottom-up energy models that support policy design of electricity end-use efficiency. We propose a classification of bottom-up energy models to analyze them from different perspectives. Next, we perform quantitative analysis to identify relevant characteristics of the models. Lastly, we examine the policy instruments and their relationship to the models.

The result of the analysis reveals that bottom-up energy models contribute to support the policy design of electricity end-use efficiency by (1) implementing different techniques and methodologies (2) allowing scenario configuration, and (3) representing the model's objectives. However, not all models implement best practices, which can jeopardize their capability to support policy design. Moreover, we realize that relevant metrics in bottom-up energy models provide pertinent information (e.g., economic and environmental) to facilitate policy design. Finally, research reveals that models for residential buildings do not employ data-driven techniques, which restricts the possibility of using a portfolio of analytics methods within the model. However, the adoption of hybrid methodologies could reverse the previous situation. The same sector presents limitations in the implementation of diverse policy instruments.

Finally, in terms of the methodology used to perform this systematic review, we present the development of tools and the execution of activities that assure the objective search of references and the increment of capacity to retrieve scientific publications. The tools and processes allow the identification of relevant articles and the establishment of semi-automatic retrieval processes. Thus, we can guarantee the quality of articles and their selection based on their scope.

In future work, we aim to analyze endogenous and exogenous variables of bottom-up energy models. Thus, we can understand their importance to policy design. Likewise, it is interesting to study the assistance of bottom-up energy models to the policy design process as decision support systems. And lastly, we expect to examine in subsequent analyses the support provided by bottom-up energy models to policy evaluation and policy implementation processes.

We urge model designers to create bottom-up energy models considering the findings of this research.

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