

# 1 Long-term energy planning and demand forecast in rural 2 areas of developing countries: classification of case 3 studies and insights for a modelling perspective

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## 14 15 **Abstract**

16 More than half a billion people are expected to still lack reliable and affordable electric energy in 2040  
17 and around 1.8 billion may remain reliant on traditional solid biomass for cooking. Long-term energy  
18 planning could help to achieve the energy access targets in developing countries, especially in remote  
19 rural areas.

20 Different studies exist on long-term rural energy planning, but the different foci, terminology and  
21 methodologies make it difficult to track their similarities, weaknesses and strengths. With this work, we  
22 aim at providing a critical analysis of peer-reviewed studies on long-term rural energy planning, to help  
23 researchers in the field move across the diverse know-how developed in the last decades.

24 The work resulted in the analysis of 126 studies and categorisation of 84 of them, under a number of  
25 rules clearly defined in the first part of the paper. The studies are then classified in two consecutive  
26 steps, first according to their type and afterwards according to the methodology they employ to  
27 forecast the energy demand, which is one of the most critical aspects when dealing with long-term rural  
28 energy planning.

29 The work also provides specific insights, useful to researchers interested in rural modelling. Few  
30 studies assume a dynamic demand over the years and most of them do not consider any evolution of  
31 the future energy load, or forecast its growth through arbitrary trends and scenarios. This however  
32 undermines the relevance of the results for the purpose of long-term planning and highlights the  
33 necessity of further developing the forecasting methodologies. We conclude that bottom-up  
34 approaches and system-dynamics seem appropriate approaches to forecast the evolution of the  
35 demand for energy in the long-term; we analyse their potential capability to tackle the context-specific  
36 complexities of rural areas and the nexus causalities among energy and socio-economic dynamics.

## 37 **Keywords:**

38  
39 Access to energy; rural energy planning; classification and analysis; energy modelling; energy  
40 demand models

## 41 **Highlights:**

- 42 – We collect case studies of rural energy planning in developing countries
- 43 – We classify rural energy planning studies according to five categories

- 44 – We focus on approaches adopted for modelling long-term energy demand
- 45 – We discuss the need to further the research on energy demand modelling for rural contexts

## 46 1. Introduction

47 Energy use and consumption are forecast to grow fast in developing contexts. Based on its New  
48 Policies Scenario [1], the International Energy Agency (IEA) estimated a rapid growth of the energy  
49 demand in sub-Saharan Africa and in rural and urban India in the next 25 years [2]. In the non-OECD  
50 regions, the total energy demand is expected to exceed the OECD regions' one by 89% in 2040 [3],  
51 especially in Southeast Asia, China and India. In developing countries (DCs), energy access-oriented  
52 policies and actions may contribute to the growth of the global energy demand. The World Bank  
53 estimates that 2.6 billion people should be electrified, and 4.4 billion should be served with modern  
54 cooking services by 2030 in DCs [4]. Nevertheless, more than half a billion people, increasingly  
55 concentrated in rural areas of sub-Saharan Africa, are expected to still lack of reliable and affordable  
56 electric energy in 2040 and around 1.8 billion may remain reliant on traditional solid biomass for  
57 cooking [5]. Rural energisation is therefore expected to largely contribute to the achievement of energy  
58 access goals, since people still living without electricity and modern energy fuels will live  
59 predominantly in rural areas [6][7]. In this context, the need to develop sustainable and appropriate  
60 approaches to energy planning clearly emerges.

61 As always in energy planning, also when dealing with rural energisation plans, a sustainable and  
62 reliable approach is advised. The latter may influence the architecture and the sizing of the  
63 implemented solutions, particularly where economic resources are scarce, as Kusakana discusses [8].  
64 Much of the planning relies on good estimates of the energy demand and its evolution with time.

65 Wrong predictions could negatively impact the local socio-economic development and cause an  
66 inappropriate sizing of local energy solutions, leading to supply shortages or cost recovery failure [9].  
67 Cabral et al. [10,11] and Kivaisi [12] stressed the need to pay attention to the evolution of the  
68 electricity load when planning electrification programmes, since the marginal costs of energy services  
69 vary among supply alternatives (*i.e.* small photovoltaic (PV) systems when the load is low, grid-  
70 extension when it is high). Fuso Nerini [13] demonstrated how the cost of the energy system for  
71 reaching different tiers of electricity access (*i.e.* different levels of energy demand to satisfy) in the  
72 village of Suro Craic in the years 2010-2030 may vary from few hundreds to 8000 2010US\$. Brivio et  
73 al. [14] demonstrate that in Photovoltaic-batteries based off-grid systems, the optimal size of the  
74 components are sensitive to the load evolution pattern, especially the capacity of the battery energy  
75 storage system. Hartvigsson [9] developed a system dynamics model to show how the power supply  
76 capacity should be accurately considered based on the forecasts of electricity demand: a demand  
77 larger than the capacity installed generates lack of power availability that may affect the willingness of  
78 people to stay connected and the utility revenues. Van Ruijven et al. [15] developed a bottom-up  
79 model to assess trends in electrification over the next decades in DCs, and they demonstrated how  
80 the potential of mini-grid technologies is highly dependent on the demand level.

81 Due to highly uncertain dynamics, strong non-linear phenomena, complex diffusion mechanisms, time-  
82 adjustments of technology perceptions, and low quality and availability of data affecting such remote  
83 contexts, the long-term forecasting of energy demand in rural areas is a complex issue. This is the  
84 reason why studies on local energy planning usually tackle demand forecasts by relying on multiple  
85 scenarios that follow regional policies or international guidelines (*e.g.* the OECD Environmental  
86 Outlook as in [15] or multi-tier categorisation proposed by the World Bank as in [13]).

87 This work reviews long-term rural energy planning studies on the basis of the application and the  
88 insights they provide, rather than their structural characteristics. The aim is to provide a synthesis of  
89 strengths and weaknesses, fields of applicability and insights which do not depend on the views of the  
90 authors or the specific terminology employed. Moreover, as a novelty, we try to combine the analysis  
91 of both the "demand" and the "supply" aspects of the rural energy planning studies, stressing the need  
92 to consider the two parts of the planning as linked and interdependent. Indeed, the aspect of long-term  
93 energy demand analysis and modelling within long-term rural energy planning is a poorly discussed

94 and addressed topic in the reference literature, and we aim at opening a discussion about its  
95 importance in the field: we first introduce the approaches currently adopted to forecast long-term  
96 energy demand within the rural energy planning-based literature, and then we try to derive some  
97 useful insights and guidelines for tackling the issue in remote contexts.  
98 The work intends to inform diverse groups of audiences, from researchers to energy planners, with  
99 different sets of information, levels of technical knowledge and involvement in the implementation  
100 aspects.  
101 Section 2.1 reports the rationale and methodology we employed to carry out the review. Section 2.2  
102 proposes a multi-criteria classification for the energy planning case studies and a description of the  
103 papers reviewed, while Section 3 analyses the methodologies to forecast the evolution of the energy  
104 demand employed in local energy planning case studies and it proposes guidelines for developing  
105 appropriate approaches to model rural energy demand.

## 106 **2. Analysis of the long-term rural energy planning literature**

### 107 **2.1. Rationale and methodology**

108 Different Authors have defined *energy planning* in several ways, emphasizing multiple important  
109 aspects. In general, the literature refers to energy planning as the process aimed at developing long-  
110 term policies for supporting the development, implementation and management of local, national,  
111 regional or even global energy systems. Prasad et al. [16] quote some authors underling that any  
112 energy planning needs to foster sustainable development. They consider energy planning “as a  
113 roadmap for meeting the energy needs of a nation [which] is accomplished by considering multiple  
114 factors such as technology, economy, environment, and the society that impact the national energy  
115 issues” ([16] p. 686). Hiremath et al. [17] write that the “energy planning endeavour involves finding a  
116 set of sources and technologies in order to meet the energy demand in an optimal manner” (p. 729).  
117 Deshmukh [18] suggests that energy planning aims above all at developing an optimal plan for the  
118 allocation of energy resources, by considering future energy requirements according to several  
119 technical, economic, social and environmental criteria. Yusta and Rojas-Zarpa [19] state that “energy  
120 planning implies finding a set of sources and conversion equipment that optimally satisfy the energy  
121 demand of all activities” (p. 67). In view of the above discussion and being aware of both the policy-  
122 and design-oriented concept of energy planning, in this study we refer to energy planning as that  
123 process aimed at (i) selecting (viz. identifying, sizing and designing) conversion technologies (ii) by  
124 performing an optimisation based on appropriate criteria (viz. either strictly mathematical programming  
125 or multi-criterial analyses if dealing with less quantitative objectives) (iii) for matching a certain demand  
126 with the available energy resources. Coming from an engineering and modelling background, we  
127 decided to emphasize the importance of objective criteria in order to confer a more scientific meaning  
128 and nature to the concepts of “optimal plan /optimally” that emerged from the literature. This definition  
129 is in line with the final aim of our research, which mainly focuses on the development of appropriate  
130 models for supporting the design phase of rural off-grid energy systems.  
131 We discarded from our classification all the case studies which do not comply with the above definition  
132 of energy planning. For example, Díaz et al. [20] develop a comparative analysis between three off-  
133 grid technologies for the rural electrification of a group of families in Argentina, without introducing any  
134 optimisation criterion to select the most appropriate energy conversion system. Again, Johnson et al.  
135 [21] analyse the energy supply and use in a rural village in Mali and the dynamics of seasonal  
136 variation in the energy demand for one year, without employing any mathematical model to optimise  
137 the matching between supply and demand. Such case studies are not within the scope of the survey.  
138 In order to comprehensively investigate energy planning methods and applications (*i.e.* including input  
139 data processing, such as the load profile, and the final results), in our survey we analyse only real-life  
140 case studies or potential applications for real contexts, excluding papers that present only the  
141 theoretical methodologies. This adds value to the existing reviews and it is meant to address the  
142 research of a suitable and appropriate modelling framework for projecting the energy demand in real  
143 rural energy planning case studies. For example, Bernal-Agustin et al. [22] propose a multi-objective

144 evolutionary algorithm and a genetic algorithm to find the most appropriate hybrid energy system to  
145 minimise the costs and the unmet demand. They rely on a reference daily load profile for implementing  
146 the optimisation. However, they do not provide any details about the daily demand or potential  
147 applications, therefore their study is not classified. Gupta et al. [23–25] analyse a hybrid energy  
148 system in order to determine its cost optimal operation. In the first [23] and second part [24] of the  
149 work they develop the mathematical model for the optimisation and the necessary algorithm to control  
150 the dispatch of battery storage systems. Only the third part [25] is here classified because it describes  
151 the application and simulation of the energy system for a real case study.

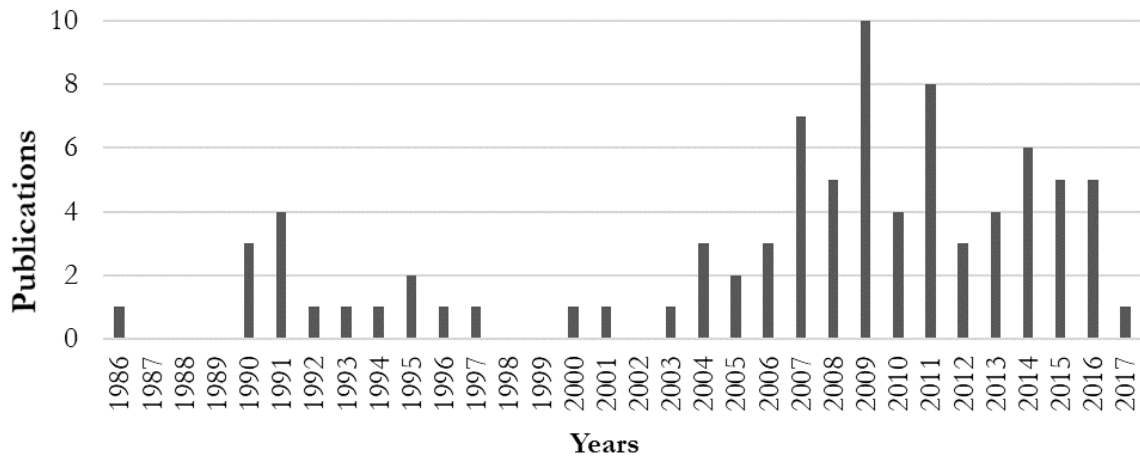
152 At a spatial level, only local rural energy planning for DCs (and BRICS) is here considered, whereby  
153 works referring to other contexts or to global and national scales are not included in the review. For  
154 example, Clark et al. [26] and Wies et al. [27] focus on a remote power system for a village in Alaska,  
155 so their studies have not been included. The same applies for Bala [28], who proposes a bottom-up  
156 approach to minimise CO<sub>2</sub> emissions for Bangladesh, but at national level. Edmonds et al. [29]  
157 develop a long-term energy-economy model for assessing alternative energy evolutions over periods  
158 of up to 100 years at a global level, accounting for CO<sub>2</sub> emissions. Parshall et al. [30] develop a  
159 national electricity planning model to guide grid expansion in countries with low pre-existing electricity  
160 coverage in Kenya. Alfaro and Miller investigate potential appropriate decentralised renewable energy  
161 schemes for Liberia at national level [31].

162 On the contrary, we do not put any restriction on the type of off-main grid system that the case studies  
163 propose: standalone systems, microgrids and distributed hybrid microgrids are considered, according  
164 to the classification given by Mandelli et al. [32]. Grid-based power is usually the least-cost option for  
165 large concentrations of household or industrial loads: it offers economies of scale, due to large fixed-  
166 cost investment in distribution lines and generation facilities. However, it is often the least attractive  
167 option at regional and village-size level [15], due to a number of economic, environmental, political,  
168 technical and social factors [32]. The selection of off-main grid case studies was not a prerogative  
169 stated at the beginning, but an outcome of the research, since they focus on rural areas where the  
170 population is highly dispersed and lives far from urban centres. For example, Zeyringer et al. [33]  
171 present an example of grid extension electrification in Kenya, comparing it with stand-alone PV  
172 systems. They find that, under current circumstances, the implementation of stand-alone PV systems  
173 is the most appropriate cost-effective solution in areas with low population density. As a matter of fact,  
174 because of high transmission and distribution costs, WEO-2013 [34] quotes that in the Universal  
175 Access scenario grid extension will be able to provide access only to 30% of rural areas. The  
176 remaining areas would rely either on mini-grids or small, stand-alone off-grid solutions.

177 The papers were selected starting from a web research on *Science Direct editorial platform* and  
178 *Scopus database*, and from references mainly taken from [19,32,35]. At the end, 126 papers have  
179 been studied and 84 have been selected for the analysis and classification.

180 Even if no range of publication date was fixed, Figure 1 shows how, among the papers selected in this  
181 study, the greatest number of publications is concentrated between 2004 and 2015.

182



183  
184 **Figure 1.** Publication on local energy planning over the years.

185 **2.2. Classification and analysis of long-term energy planning case-studies**

186 Within the energy planning literature, Prasad et al. [16] present the risks, uncertainties and errors  
 187 involved in energy planning, as well as a review of models for energy planning (*econometric models*,  
 188 *optimisation models*, *simulation models* and the related computer-assisted tools). In the context of  
 189 rural electrification, Mandelli et al. [32] propose the most recent review of the scientific literature  
 190 focused on off-grid systems according to five main research areas including *models and methods for*  
 191 *simulation and sizing*. Hiremath et al. [17] present a classification of energy models for decentralised  
 192 energy planning: *optimisation models*, *decentralised energy models*, *energy supply/demand driven*  
 193 *models*, *energy and environmental planning models*, *resource energy planning models* and *models*  
 194 *based on neural networks*. The same Authors [36] published more recently a review of possible  
 195 decentralised renewable energy options for the Indian context. The review includes case studies of  
 196 successful deployment of such options and opportunities (*e.g.* job creation) arising from the  
 197 decentralisation of electricity generation. Nicole van Beeck [37] presents a decision support method  
 198 for selecting appropriate energy systems for regions experiencing rapid growth, such as villages in  
 199 developing countries. The Author proposes nine criteria to classify energy models: *purposes of energy*  
 200 *models*, *model structure*, *analytical approach (bottom-up vs. top-down)*, *underling methodology*,  
 201 *mathematical approach*, *geographical coverage*, *sectoral coverage*, *time horizon*, *data requirements*.  
 202 Yusta et al. [38] investigate the most utilised multi-criteria decision methods for electrification planning  
 203 in rural areas and they review approximately 120 publications related to energy planning [19], focusing  
 204 mainly on 50 cases studies of decentralised power supply plans. They classify them according to  
 205 *referring country*, *mathematical model*, *methodology application*, *adopted criteria*, *implemented*  
 206 *technologies*, and *target population*. Deshmuk [18] discusses how to develop an Integrated  
 207 Renewable Energy System (IRES) to find the optimal energy resource allocation in energy planning  
 208 processes, and suggests a classification of energy planning models based on *methodology adopted*  
 209 *(bottom-up vs. top-down)*, *spatial coverage*, *sectoral coverage* and *temporal coverage*. Trotter et al.  
 210 [39] present a well-written comprehensive and systematic review of electricity planning in sub-Saharan  
 211 Africa. They consider a broad definition of planning – i.e. “an integrated approach of analysing an  
 212 economically, technologically, environmentally, socially and/or politically suitable equilibrium between  
 213 electricity demand of a given unit of analysis and different available supply options across at least one  
 214 element of the electrification value chain” ([39] p. 1189). They review the literature according to three  
 215 categories: *value chain depth*, *decision criteria used* and *number of different decision alternatives*.  
 216 Based on Deshmuk [18], Yusta et al. [19] and Nicole van Beeck [37], we introduce an extended and  
 217 more comprehensive classification of more than 80 energy planning case studies in six categories: (i)  
 218 spatial coverage, (ii) planning horizon, (iii) energy vector, (iv) energy uses and (v) decision criteria  
 219 mathematical models. Categories (i), (ii) and (iv) are selected from Deshmuk [18] and Nicole van

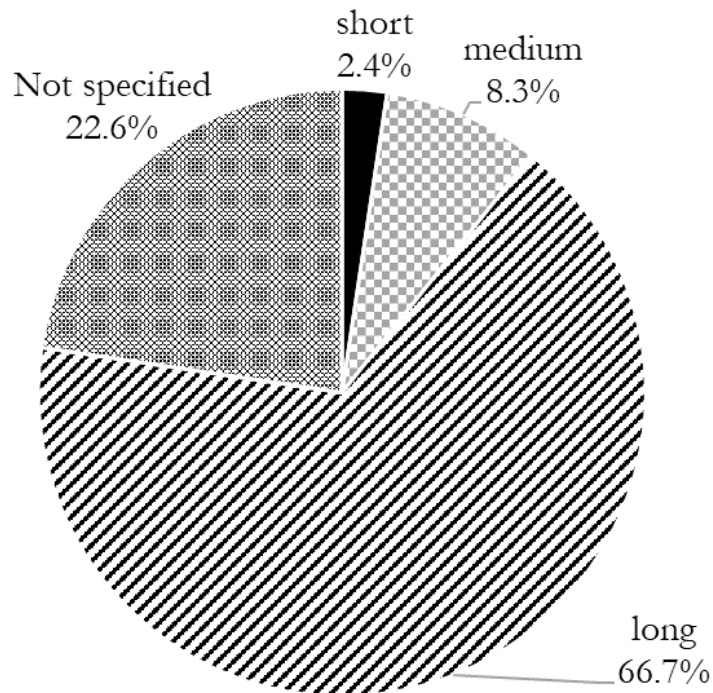
220 Beeck [37]. Category (v) is based on Yusta et al. [19]. Appendix A reports a complete overview of the  
221 classification adopted for the collected case studies. In the following paragraph, we give an insight for  
222 each of the six categories. For each one we report some examples of case studies and the related  
223 models.  
224 With this categorisation, we aim at proposing a framework containing all the most relevant aspects  
225 and information that rural energy planning studies should consider, state, and discuss. We also look at  
226 the topics that would need more investigation and might open new research opportunities, especially  
227 from an energy modelling perspective.

### 228 **2.2.1. Spatial coverage: local and regional coverage**

229 Within this category, studies are classified based on the extension of the geographical domain they  
230 consider: *local coverage* considers a village, a community, and a group of small villages [40–42] or set  
231 of houses [25,43] located in the same region of the same nation; *regional coverage* includes islands,  
232 big cities or institutional divisions according to linguistic boundaries or morphological constraints. As  
233 already stated, national and global case studies are not covered in our analysis.  
234 Authors identify and specify the spatial coverage of their work in different ways. Himri et al. [44]  
235 present a study for a remote village in Algeria, specifying the number of consumers living in the area.  
236 Musgrove [45] develops a dynamic programming model to find the optimal operating strategy for  
237 satisfying an electrical load of 1 kW, without specifying the number or type of user(s). Salehin et al.  
238 [46] combines a HOMER-based techno-economic optimisation with a RETScreen-based energy  
239 scenario analysis for assessing a PV-Diesel and a Wind-Diesel power system in a small locality of  
240 1000 people in Kutubdia Island, Bangladesh. Gupta et al. [47] study a hybrid energy system for the  
241 Juanpur block in India, specifying the extension of the location and the number of households. Silva et  
242 al. [48] focus on the applicability of multi-objective methods to assess the introduction of renewable  
243 technologies for general “Non-interconnected Zones” in Colombia. Nakata and Kanagawa [49] apply  
244 the META-Net economic modelling tool to analyse the future energy supply options and end-use  
245 devices for the rural areas of Assam region, India. Zeyringer et al. [33] analyse the options of grid  
246 extension and stand-alone photovoltaic systems for the electrification of Kenya, dividing the entire  
247 national area in cells that vary in coverage, from local to regional.  
248 From this first categorisation, it emerges that about 78% of the cases analysed are *local* energy  
249 planning, suggesting a lack of *regional* studies. Moreover, in some cases the spatial coverage of the  
250 study is vaguely defined. This might prevent the extension of the approach and the findings to other  
251 similar cases of energy planning in analogous contexts. From the analysis of the spatial coverage of  
252 all the case studies, it emerges that modelling frameworks for local planning (e.g. HOMER ®) allow  
253 detailed technical aspects of the planned energy systems to be analysed and taken into account; on  
254 the other hand, regional planning mainly concerns the selection of the optimal energy supply strategy,  
255 such as the identification of the energy mix and the solution of the off- / on-grid dilemma.

### 256 **2.2.2. Planning horizon: short, medium and long term**

257 The second category refers to the time scale considered for implementing the energy planning. Four  
258 subcategories are identified: *short-term* (from one month to one year), *medium-term* (from one to ten  
259 years), *long-term* (beyond fifteen years) and *not-specified* term. The distribution of the works between  
260 these subcategories is reported in Figure 2.  
261



**Figure 2.** Classification of case studies: Planning Horizon.

262  
263

264 Authors usually introduce the planning horizon in two different ways: some specify explicitly the  
 265 lifespan of the project or lifetime of the energy system; others do not point out the planning period but  
 266 report the lifetime of the components such as PV, diesel gen-set or wind turbine used to calculate the  
 267 net present value or the discounted costs of the system. For example, Haddadi et al. [50] specify three  
 268 different lifetimes for the systems implemented, equal to 10, 15 and 20 years. Similarly, Sen et al. [51]  
 269 indicate a project's lifetime of 25 years. On the contrary, Silva et al. [48] do not point out the lifetime of  
 270 the entire project but make the lifetime of the technologies explicit, in order to calculate the net present  
 271 cost of the renewable energy system. Daud et al. [52] state clearly that the life cycle period of the  
 272 system is assumed to be the maximum lifetime of the main components of the system. In cases where  
 273 the project lifetime is not indicated, the maximum lifetime between all the system components defines  
 274 the planning horizon of the study. This assumption is especially adopted to describe case studies  
 275 where technical data of system components are listed, as Arun et al. do in [53].

276 Papers that do not specify any information for deriving the planning horizon are accounted for in the  
 277 not-specified category. For example, Kanase-Patil et al. [54] apply the Integrated Renewable Energy  
 278 Optimization Model (IREOM) for the electrification of dense forest areas in India in order to minimise  
 279 the cost of energy generation over an amortisation period of  $n$  years. Again, Gupta et al. [47] generally  
 280 note that the unit costs are calculated on the basis of the lifetime of the plants, without indicating a  
 281 precise value.

282 This analysis highlights that about 67% of the studies refer to long-term energy planning, while almost  
 283 one-quarter does not specify enough information to derive the planning horizon. This lack of  
 284 information about the time horizon undermines the robustness of the planning results, since it prevents  
 285 their replicability, as well as any uncertainty analysis on the evolution of the techno-economic  
 286 parameters (e.g. energy demand, costs, efficiency). The classification of the case studies based on  
 287 their planning horizon provides also useful insights about the details achievable by each energy  
 288 model: short-term energy models allow the analyst to consider more precisely short time steps  
 289 (seconds or minutes), specific operation constraints of the analysed energy systems and their  
 290 response in case of unexpected conditions and phenomena (e.g. fluctuations, changes in weather  
 291 conditions, variabilities of renewable resources). Long-term models usually rely on longer time  
 292 resolutions (hours, days, weeks). This could prevent the analysis of short-term dynamics but allows

293 the introduction of long-term variables (e.g. energy demands, useful life-time of the technologies,  
294 discount rates) that are pivotal to more complete economic analyses and sizing procedures.

### 295 **2.2.3. Energy vector: electricity, thermal energy and oil products**

296 The “energy vector” category classifies the case studies based on the energy output of the power  
297 systems subject to the planning. Three types of energy vector have been defined: *electricity, thermal*  
298 *energy and oil products*.

299 Electricity results as the most considered energy vector in the case studies (Figure 3), especially  
300 within those focusing on rural electricity planning and employing HOMER ® software for the optimal  
301 sizing of the off-grid system [40,44,46,55–72].

302 The thermal energy vector is the second most considered in the case studies, especially for the  
303 residential sector. This sub-category includes both thermal energy for space heating and cooking,  
304 often produced by systems fuelled by non-commercial energy (e.g. biomass and agricultural residues  
305 for cooking). For example, Malik and Satsangi [73] apply mixed integer/linear programming for  
306 optimizing the supply of energy for cooking in the rural areas in Wardha District, India. Joshi et al. [41]  
307 investigate the most appropriate fuels for cooking and for space heating in three villages of different  
308 zones of rural Nepal, among fuel wood, agriculture residues and animal dung.

309 Many case studies implement energy planning by considering more than one energy vector. Devadas  
310 [74] presents a linear programming-based model to optimally allocate energy resources to different  
311 end-uses such as household consumption, agriculture and transport, considering electricity for  
312 irrigation and lighting, liquefied petroleum gas for cooking, kerosene for the lamps of lower income  
313 consumers and organic and inorganic fertilizers for farming activities. Srinivasan and Balachandra [75]  
314 identify the most appropriate energy conversion technologies and non-commercial fuels for producing  
315 electricity for lighting and energy for cooking and thermal purposes. Hiremath et al. [76] optimise a  
316 decentralised bioenergy system to produce biogas for cooking and biomass for power generation.  
317 Fuso Nerini et al. [13] study the cost optimal energy supply options for different scenarios of energy  
318 demand in the village of Suro Craic, Timor Leste. Howells et al. [77] employ a MARKAL-TIMES model  
319 to plan household energy services in an African village considering both electricity and thermal energy  
320 for cooking.

321 In accordance with Pachauri et al. [78], this review indicates that rural energy planning studies mainly  
322 concern electricity planning, revealing that little quantitative analysis focuses on the other energy  
323 vectors. More comprehensive approaches would be needed to tackle all the challenges concerning  
324 sustainable rural energy planning, including the study of options to supply energy for cooking. This  
325 vector is highly prioritised in the Sustainable Energy for All (SE4All) global Agenda [79], as one of the  
326 pillars for achieving the SDG7 [80].



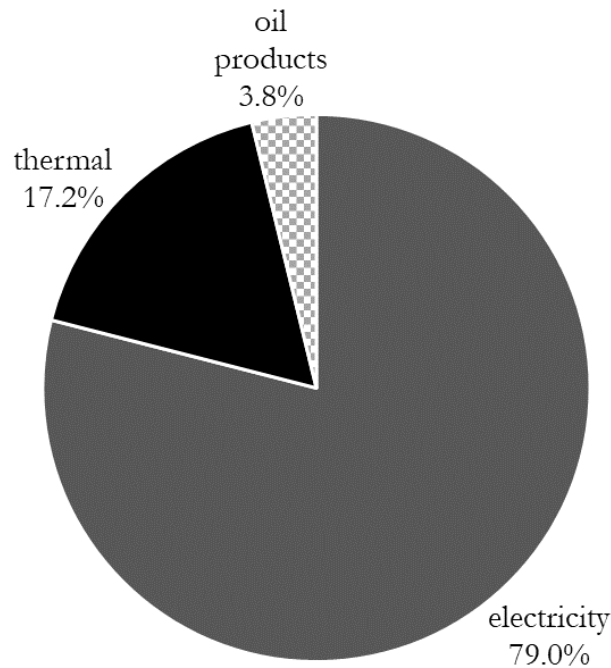


Figure 3. Classification of case studies: Energy Vector.

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329 **2.2.4. Decision criteria mathematical models: Linear Programming (LP), Multi-Criteria**  
 330 **Decision Making (MCDM), Multi-Objective Programming (MOP), Non- Linear**  
 331 **Programming (NLP), Dynamic Programming (DP), Enumerative Optimisation (EO)**

332 In this sub-section, we examine the optimisation methodology lying behind the planning procedure. In  
 333 accordance with Yusta and Rojas-Zerpa [19], decision criteria analysis has been classified into seven  
 334 sub-categories (classes of models): *Linear Programming (LP)*, *Multi-Criteria Decision Making*  
 335 *(MCDM)*, *Multi-Objective Programming (MOP)*, *Non- Linear Programming (NLP)*, *Dynamic*  
 336 *Programming (DP)*, *Enumerative Optimisation (EO)* and *other*.

337 LP is used to optimise a linear objective function subject to a set of linear constraints. In the analysed  
 338 case studies, it is especially employed to minimise the cost of matching supply and demand  
 339 [58,81,82]. The category includes also models using Mixed Integer Linear Programming (MILP). There  
 340 are several modelling languages: LINGO is a modelling software developed by *Lindo Systems Inc.*  
 341 and it is used by Kanase-Patil et al. [40] to calculate the cost of energy for an off- grid system in India.  
 342 Fuso Nerini et al. [13] used OSeMOSYS [83], a linear model generator written in GNU MathProg  
 343 language – a subset of the AMPL (A Mathematical Programming Language) –, to carry out the energy  
 344 planning of Suro Craic village in Timor Leste.

345 MCDM solves problems involving more than one criterion of evaluation such as cost or price,  
 346 efficiency and emissions. Analytic Hierarchic Process (AHP), Compromise Programming (CP), Goal  
 347 Programming (GP), and Elimination and Choice Expressing Reality (ELECTRE) are MCDM-based  
 348 techniques. Semaoui et al. [43] developed a Simulink-based model for the optimal sizing of a stand-  
 349 alone photovoltaic system in Algeria, relying on a (i) reliability and (ii) economic criterion for the  
 350 optimisation. Cherni et al. [84] implemented their multi-criteria decision-support system SURE to  
 351 calculate the most appropriate set of energy alternatives for supplying power to a rural Colombian  
 352 community, considering physical, human, social, natural and financial assets.

353 MOP is a method for solving optimisation problems with more than one objective function. For  
 354 example, Hiremath et al. [76] set seven objective functions in their optimisation problem: minimisation  
 355 of cost, maximisation of system efficiency, minimisation of use of petroleum products, maximisation of  
 356 use of locally available resources, maximisation of job creation, minimisation of CO<sub>x</sub>, NO<sub>x</sub>, and SO<sub>x</sub>  
 357 emissions and maximisation of reliability.

358 NLP includes optimisation problems whose variables and constraints are linked by non-linear  
359 relations. Ashok [85] uses a Quasi-Newton algorithm to determine the optimal number of renewable  
360 energy units for a typical rural community in India. The META-Net economic modelling tool adopted by  
361 Nakata and Kanagawa [49] to analyse energy options in rural India is based on a NLP and partial  
362 equilibrium tool. Segurado et al. [86] relied on H2RES software to plan the future power generation for  
363 S. Vincent Island in Cape Verde; the model is based on a single-objective optimisation, i.e. the  
364 minimisation of the Levelised Cost of Energy (LCOE), subject to nonlinear relations and constraints.  
365 DP is a technique for solving complex problems by splitting them into a sequence of smaller sub-  
366 problems, resolving and storing them in a data structure. Thus, DP does not identify a single  
367 optimisation algorithm: a variety of optimisation techniques can be employed to solve particular  
368 aspects of the main problem. It is applicable to problems that require a sequence of interrelated  
369 decisions to be made. Nahman and Spirić [87] determine the optimal long-term planning of various  
370 characteristic types of rural networks using a constrained DP technique. Bowe and Dapkus [88]  
371 formulate the problem of power systems expansion planning of a small utility in Midwest as a Markov  
372 decision process, and they use stochastic DP to solve the model. Das et al. [89] use DP to define the  
373 optimal investment plan for renewable energy technologies in Gajalia village, South-West Bengal.  
374 More recently, EO stands out as a methodology of practical interest and straightforward application.  
375 Combinatorial optimisation models are also included in this category. This approach calculates  
376 numerically the optimal solutions based on one or more objectives. Usually, the objective is to  
377 minimise the cost of energy supply, by modifying the size of the supply technologies under a number  
378 of constraints (e.g. the availability of renewable resources). HOMER ® falls within this category: given  
379 the user-specified constraints and lower and upper limits on the size of the system the tool simulates  
380 every possible system configuration within the search space. The HOMER Pro's Optimizer <sup>TM</sup>  
381 facilitates this operation, selecting the solution that satisfies the lowest total net present cost [90].  
382 Türkay et al. [55] apply HOMER ® to find the lowest net present value for a stand-alone system  
383 composed of solar photovoltaic, wind turbines and fuel cells to supply electricity for a university in  
384 Turkey. Kolhe et al. [57] apply the same tool for optimally sizing an off-grid hybrid renewable energy  
385 system for electrifying a rural community in Sri Lanka. Akella et al. [58] compared LINDO ® and  
386 HOMER ® – respectively based on LP/NLP and EO optimisation methods – to define the optimal  
387 IRES for the Jaunpur block of Uttaranchal state of India. Mandelli et al. [91] develop a novel EO-based  
388 methodology for sizing PV-batteries power systems, which embraces uncertainty on load profiles.  
389 They apply it to electricity planning in a peri-urban area of Uganda.  
390 Case studies that do not fit anyone of the classes or do not provide enough information are identified  
391 as "Others". For example, Phrakonkham et al. [92] minimises the annualised cost of energy for a  
392 remote village in Northern Laos with a genetic algorithm implemented in Matlab ®. Rana et al. [93] use  
393 an intuitive sizing method. They calculate and identify the system with the lowest total life cycle cost of  
394 six combinations of three possible technology alternatives (*i.e.* standalone PV, biogas system, gasifier  
395 system) to optimally match the energy supply and demand. Segurado et al. [86] rely on H2RES  
396 software to maximise the penetration of renewable energy sources in the electricity system of S.  
397 Vicente Island in Cape Verde and they describe it simply as a "simulation tool".  
398 Figure 4 illustrates the distribution of the reviewed works across the described decision criteria  
399 methods.  
400

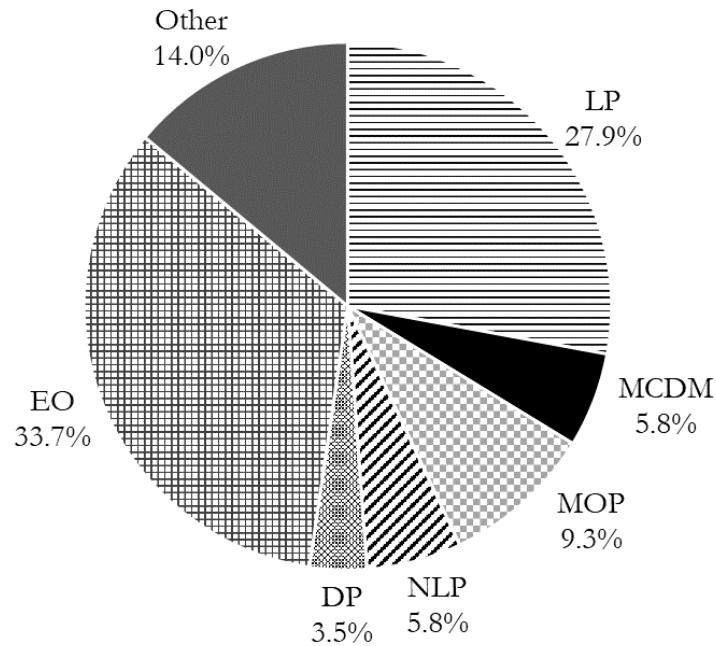


Figure 4. Classification of case studies: Decision criteria mathematical models.

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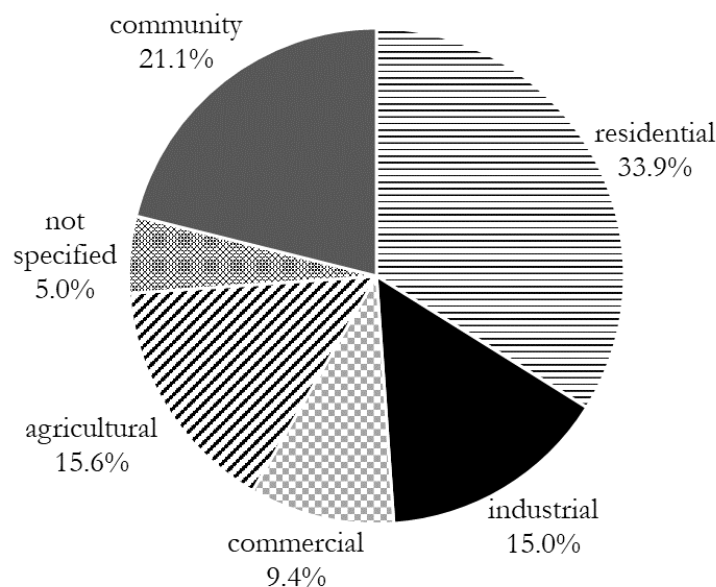
403 EO results to be the most used mathematical method. It is adopted in 33.7% of the case studies,  
 404 especially those that rely on HOMER ®. LP follows, used in 27.9% of the case studies. LP is based on  
 405 analytical optimisation, requiring less computational time and effort than EO methods. On the other  
 406 hand, EO is not constrained by the need to set only linear equations, sometime overly simplistic [94];  
 407 they therefore result in a better representation of the actual dynamics and phenomena that  
 408 characterise the operation of energy systems (e.g. the charge-discharge dynamics inside the  
 409 batteries).

410 This part of the review results suggests that the literature has been mainly limited to mono-objective  
 411 optimisation models so far. Considering the multifaceted issue of sustainable rural energy planning  
 412 [39] – which includes important socio-economic and environmental aspects, such as technology  
 413 appropriateness, indoor air pollution, local know-how and capabilities –, MCDM and MOP models may  
 414 provide more comprehensive frameworks for rural energy planning. Interesting options can consider  
 415 the soft-linking with behavioural approaches, in order to take into account complex social aspects. As  
 416 a pioneer example in this field, Moresino et al. [95] couple OSeMOSYS with a share of choice in order  
 417 to take into account the consumers' real behaviour. In their case study, they focus on the consumer's  
 418 preferences regarding the purchase and use of electric bulbs.

419 **2.2.5. Energy uses: residential, communitarian, agricultural, industrial, commercial and not-**  
 420 **specified**

421 We classify the case studies based on both the type of energy users and the end-use of energy:  
 422 *residential, communitarian, agricultural, industrial and commercial and not-specified*. In accordance  
 423 with IEA's definition [96], such categories are the most comprehensive ones of all energy uses. The  
 424 energy consumption for the residential sector includes demand for lighting, cooking and powering  
 425 domestic appliances such as radios, televisions, fans, etc. The communitarian use of energy refers to  
 426 schools, medical centres, radio stations, small shops, churches, and restaurants. Ferrer-Martí et al.  
 427 [97] design an electrification plan for a community in Peru, considering households and five institutions  
 428 as direct beneficiaries, namely the church, the school, the health-centre, restaurants and shops. The  
 429 agricultural sector includes energy for farming activities: pumping water, ploughing, supplying tractors  
 430 and other agricultural uses. The industrial sector considers rural industries and income generating  
 431 activities, such as grain mills, coal kilns, small vans for products transportations, etc. The energy

432 demand for the commercial sector refers to energy used for all the activities that need roads,  
 433 telecommunication infrastructure, water and irrigation networks, bank and credits facilities;  
 434 transportation (unless otherwise specified) is included as well, with the hypothesis that few people use  
 435 cars or mini-vans as private use in rural contexts.  
 436 Very few case studies specify the sector covered by the planning [58,71,91], but they provide a the  
 437 description of the type of technology and appliance to supply [13,88] or the end-uses of energy [77,98]  
 438 – such as lighting, cooking, pumping, heating, cooling and transportation –, whence the demand  
 439 sector is derived. Mandelli et al. [91,99] simulated the planning of a PV-based power system for a rural  
 440 village in Uganda, investigating the effect of the uncertainty of the load profile on the optimum sizing;  
 441 they employed a novel stochastic tool called “LoadProGen” to derive the load curves, which requires  
 442 the definition of all the classes of users as input and consequently their end-use load profile. Amutha  
 443 [71] explicitly estimates the electricity uses for the households, the industries, the agricultural activities,  
 444 and the local Base Transceiver Station (BTS) (*viz.* a device that facilitates wireless communication) for  
 445 the electricity planning of a remote Indian village.  
 446 Figure 5 illustrates how case studies are distributed among the five demand sectors.  
 447



448  
 449

**Figure 5.** Classification of case studies into the five Demand Sectors.

450 It emerges that energy planning deals more with residential demand, in accordance with  
 451 Bhattacharyya [35], who stated that “the demand in rural areas arises mainly from the use of domestic  
 452 appliances” (p. 678). However, the literature concerning the nexus between energy and local  
 453 development shows the need to increase the focus on the industrial use of energy, elsewhere called  
 454 *productive use of energy*. Specifically, it indicates that access to energy, when it is supported by  
 455 complementary activities – e.g. educational activities, capacity building and awareness campaigns –,  
 456 can be a pivotal driver in developing new business [100–107], with a consequent increase in the  
 457 industrial energy demand. In line with this finding, Homer Pro ® has a new interesting feature, which  
 458 allows the user to select default “Commercial” and “Industrial” types of load in the simulation.

### 459 **3. Approaches to forecast the long-term evolution of the energy demand**

460 This section focuses on methods and approaches for the long-term forecasting of energy demand,  
 461 which is a pivotal aspect for implementing a reliable and appropriate planning of the energy supply  
 462 options, as discussed in the Introduction [9–14].

### 463 3.1. Overview of energy demand models for rural energy planning

464 The scientific literature has addressed the classification of models to forecast the energy demand.  
465 Bhattacharyya and Timilsina [108,109] propose a literature review of existing energy demand  
466 forecasting methods and highlight the methodological diversities among them. Their purpose is to  
467 investigate whether the existing energy demand models are appropriate for capturing the specific  
468 features of developing countries. They find that mainly two approaches are used: econometric (or top-  
469 down) and end-use (bottom-up) accounting; the latter is able to produce more realistic projections as  
470 compared to the former; on the other hand, it suffers from data deficiencies ([109] p. 1979), while  
471 econometric accounting does not. Suganthi et al. [110] present a comprehensive review of the various  
472 energy demand models, as well as applications for both developing and developed countries. Swan et  
473 al. [111] focus on the residential sector to present a review of existing approaches to model energy  
474 household consumption, classifying them into top-down and bottom-up approaches.  
475 Among the existing reviews, very few applications of energy models for forecasting energy demand  
476 refer to rural contexts: Hartvigsson [112] developed an end-use system dynamics model to project the  
477 electricity demand of a rural community of Tanzania by accounting for the nexus between income,  
478 economic growth and electricity needs. S. Mustonen [113] built an end-use LEAP (*Long-range Energy*  
479 *Alternative Planning System*)-based model to generate long-term scenarios of energy demand  
480 evolution for a rural village in Lao People's Democratic Republic, for a time domain from 2006 to 2030.  
481 Van Ruijven et al. [114] developed a bottom-up simulation model for investigating the growth of  
482 household energy demand in India and Daioglou et al. [115] extended it to other emerging regions:  
483 China, South East Asia, South Africa and Brazil. They named it global residential energy model  
484 (REMG) and applied it for both rural and urban areas. Fuso Nerini et al. [13] modelled 4 scenarios of  
485 energy demand growth in the rural village of Suro Craic in Timor Leste, based on the ESMAP/World  
486 Bank multi-Tier framework for measuring energy access and the long-term objectives set by the  
487 Timorese government.  
488 In this section, we assess how the existing approaches for long-term forecasting of the energy  
489 demand are employed in the previously reviewed case studies, in the attempt to derive insights and  
490 guidelines for supporting future rural energy planning studies in DCs.

### 491 3.2. Energy demand forecasting approaches: categorisation and adoption

492 Few case studies explicitly state the model adopted to predict the energy demand, like for instance  
493 Malik et al. [42,73]. We classified the others based on the mathematical forecasting approach  
494 adopted; we identified eight categories of long-term energy demand forecasting approaches: *fixed*  
495 *load*, *arbitrary trend*, *scenarios*, *regression*, *time-series*, *extrapolation*, *system dynamics* and  
496 *input/output (I/O)*. Regression, time-series and I/O approaches refer to the classification proposed by  
497 Suganthi et al. [110]; the others have been proposed by the authors and refer to the specific function  
498 or mathematical technique adopted.  
499 Appendix B reports a complete overview of the categorisation adopted for the collected case studies.  
500 The *fixed load* category is introduced for those energy planning case studies that consider a fixed  
501 value of energy load – i.e. no evolution of energy consumption – along all the planning horizon. For  
502 example, Zhang et al. [82] consider a constant electricity demand throughout the whole lifetime of the  
503 system (15 years) and they generate random weekly load profiles based on typical values of load for  
504 rural villages of Southeast Asia. Borhanazad [116] develop a MOP-based planning of three micro-  
505 grids in rural Iran. Here, they consider a constant hourly load profile for a typical rural area ([116] p.  
506 300), derived by local assessments, without considering any evolution along the planning period.  
507 Cherni et al. [84] propose a model to supply sustainable energy for a community in Colombia. They do  
508 not introduce any demand forecasting model but they state that the energy system is designed to  
509 support a potential growth of the community and its electric consumption. Almost all the case studies  
510 that employ HOMER ® software to design electricity microgrids belong to this category [40,44,46,55–  
511 72], since the software considers a fixed load curve along the planning horizon, and the only variability

512 lies at a daily and seasonal level. Also case studies that do not specify how they project the demand  
513 along the planning horizon are considered within the 'fixed load' category. For instance, Tegani et al.  
514 [117] apply a genetic algorithm to size a hybrid wind/PV/diesel power system for a small isolated area  
515 of few houses in Algeria without reporting any information about the evolution of the load along the  
516 lifetime of the system.

517 The *arbitrary trend* method is characterised by the assumption that the energy demand would evolve  
518 with at a constant pace during each year of the planning; the trend is often estimated from historical  
519 data series, as in [13,118–120], derived from local data, national plans and "goals" of energy access.  
520 Such arbitrary trends are frequently combined with multiple scenarios of energy demand. Fuso Nerini  
521 et al. [13] set arbitrary trends of energy demand growth in the rural village of Suro Craic depending on  
522 the different Tiers of electricity access defined by the World Bank [121]. Domenech et al. [97]  
523 investigated the current energy demand of a community of Alto Peru with local surveys. They derived  
524 arbitrary trends of growth from considerations on the "development of small productive activities  
525 and/or enjoyment of some domestic comforts" ([97] p. 280). For a case study focusing on India,  
526 Nakata and Kanagawa [49] assume that the total energy demand increases linearly during the  
527 planning horizon according to the expected annual growth of population in the country: 1.4% from CIA  
528 data in 2015.

529 The *scenario-based* approach refers to a set of descriptive pathways that indicate how future events  
530 may occur. It is a particularly suitable method in contexts characterised by high uncertainty. A number  
531 of case studies adopted this approach to develop possible long-term pathways of energy demand  
532 evolution: Ferrer-Martí et al. [122] couple a "low-demand" scenario characterised by constant demand  
533 for energy for households, the school and a health centre, and a "high-demand" scenario to consider a  
534 wider fulfilment of the basic needs and possible production uses. Nayar et al. [70] use HOMER ® to  
535 design an innovative wind/PV/diesel hybrid system for three remote islands in the Republic of  
536 Maldives. They gather data from monthly records and by evaluating the load profile for a period of one  
537 day, and they state that "several scenarios of [...] load growth were examined" (p. 1079).

538 The *regression* models perform the forecast through a regression function where a dependent variable  
539 is obtained by a combination of some parameters or coefficients and independent variables. The  
540 regression function is usually linear and the parameters are usually estimated from data with the least-  
541 squares technique. Zeyringer et al. [33] implement a regression and Tobit model for evaluating the  
542 monthly electricity demand per household as a function of a number of independent variables. These  
543 are non-food expenditures per household per month, the number of servants employed in the  
544 household, the flush toilet as main toilet facility, the age of the household head, the formal education  
545 of the household head and the number of people living in the household. For the regression, they use  
546 data from a 2005/2006 survey, and they project the demand to 2020 by employing forecasts of future  
547 GDP (rural, urban), population (rural, urban), and share of educated population (over 15 years of age).

548 *Time-series* models use historical panel data for extrapolating the future energy requirement. This  
549 marks a difference with the regression analysis, which investigates how the current values of one or  
550 more independent variables can affect another current or future dependent parameter. Different  
551 techniques are used in time-series models to predict the electricity demand: simple first-order  
552 autoregressive time-series models, logistic curves, Markov models and other models for technology  
553 diffusion, like Gompertz. The results of these sophisticated methods seem to depend on the structure  
554 of the model itself and the strategies employed for data analysis. Bowe and Dapkus [88] developed a  
555 Markov model for solving the problem of power systems expansion planning, simulating a case study  
556 of a small utility in Midwest in the '90s., In this case, the complexity, uncertainty and dynamics of the  
557 problem affect also the future demand levels.

558 *System dynamics (SD)* models are used to capture the nonlinear behaviour of complex systems over  
559 time, by relying on the use of causal and feedback relationships. SD models are characterised by  
560 stocks, which are the state variables of the dynamical system, and their inflows and outflows (rates),  
561 which increase or decrease the value in the stock. In the field of rural electrification, Steel [123]  
562 developed a SD model to simulate the decision-making process of electricity consumers in rural  
563 Kenya, while choosing between grid and off-grid power options. Jordan [124] uses SD to compute  
564 endogenously the electricity demand in a long-term power capacity expansion model for Tanzania.

565 Hartvigsson et al. [9] attempt to study how the initial planning of capacity generation affects cost-  
566 recovery, electricity usage and user diffusion in rural areas. Zhang and Cao [125] simulate the nexus  
567 between rural economic development, social development (*viz.* growth in population) and energy  
568 consumption to analyse the future energy supply mix for a rural Chinese region. Among the analysed  
569 case studies of rural energy planning, only Zhen [126] applied a SD approach to model energy  
570 demand: he developed a model to predict the developmental changes of the energy supply and  
571 demand for a rural village in the North China.

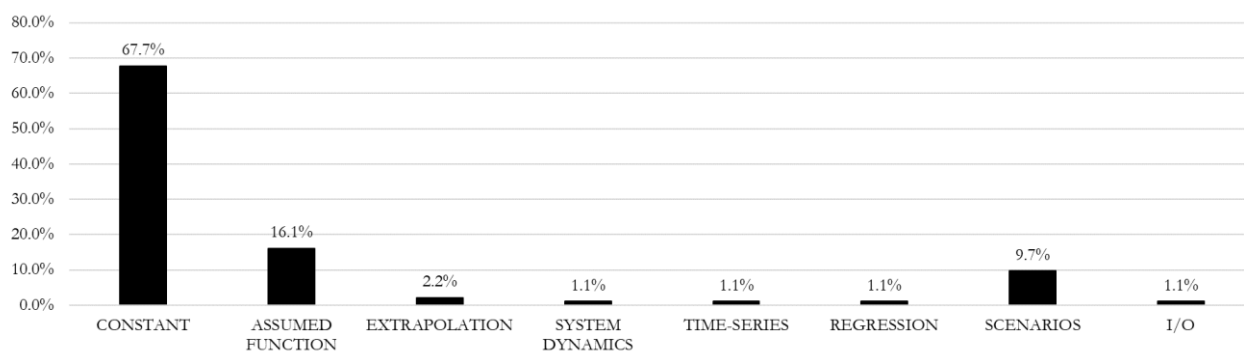
572 The *Extrapolation* technique corresponds to the method used by Malik et al. [42,73], which  
573 approximates data of future energy consumption by a probability distribution function starting from  
574 historical surveys. We did not find any other use of this technique in other cases studies, probably due  
575 to the problem of data scarcity, which prevents the use of this method in studies of rural energy  
576 planning.

577 *Input-output* models (I/O) have long been used for macro-economic and top-down analysis, with  
578 scarce application to local energy planning. They are usually not employed for modelling informal  
579 activities and non-monetary transactions, due to the lack of reliable data. Subhash et al. [127] carry  
580 out an energy planning for an Indian village cluster by developing an I/O model, which adopts inter-  
581 sectorial relations for projecting sector scenarios of the economy in the long-term.

### 582 3.3. Observations from literature and guidelines to forecast rural energy demand

583 Figure 6 summarises the distribution of the reviewed studies across the different demand forecasting  
584 approaches. It clearly emerges that two thirds of the case studies do not consider the variation of  
585 demand over the planning horizon, weakening the reliability and robustness of the design phase of the  
586 planning, especially for long-term approaches. One-third of the reviewed case studies employ HOMER  
587 ® software or its improvements to carry out the electricity planning; here, the electricity demand is fed  
588 as a daily average load profile, with the possibility to introduce a daily and monthly variability;  
589 however, no variability over the years can be introduced. Only Prasad and Natarajan [128] justify this  
590 modelling choice due to the fact that the surveyed variation of the distributions of the load resulted  
591 insignificant between the period 2000 and 2004 for the site Pompuhar, in India. Among the case  
592 studies with a long-term planning horizon, our study reveals that only 23% of them apply at least one  
593 of the remaining forecast techniques for projecting energy demand. Among these, the most used  
594 approach assumes a fixed growth every year (*arbitrary trend*) justified by previous studies, historical  
595 trends or specific assumptions, that may fail in capturing the complexities behind the evolution of  
596 energy demand in rural contexts. Therefore, they are often combined with a *scenario*-based approach,  
597 which is very useful to deal with uncertainties in the demand; nevertheless, the use of the *scenario*-  
598 based approach must be compatible – at reasonable computational effort and time – with the decision  
599 criteria mathematical models employed for the energy planning.

600



601

602

**Figure 6.** Percentage of energy demand forecasting approaches adopted in the case studies.

603

604 These results highlight that the use of appropriate and reliable models for long-term energy demand  
 605 forecast in rural energy planning studies is quite limited. Based on the literature, we try to propose  
 606 some guidelines that aim at enhancing the future research on this topic. When modelling energy  
 607 demand in DCs, Urban et al. [129] list the main characteristics of the energy system of developing  
 608 countries that should be captured by energy models: the supply shortages, the transition from  
 609 traditional to commercial fuels, the role of income distribution, the urban/rural split, the  
 610 underdeveloped markets and informal activities, structural changes in the economy and subsidies.  
 611 Bhattacharyya and Timilsina [109] criticise most global energy models that forecast future residential  
 612 energy demand based on relatively simple relationships between energy consumption and income or  
 613 GDP per capita, since they neglect such specific dynamics of developing countries and use aggregate  
 614 macro-data. Table 1 presents an abstract of the main features, strengths and weaknesses of the two  
 615 most diffuse approaches discussed by Bhattacharyya and Timilsina: top-down or econometric and  
 bottom-up or end-use approach.

616

**Table 1.** Characteristics of bottom-up and top-down models.

	Bottom-up	Top-down
<b>Strength</b>	<ul style="list-style-type: none"> <li>- detailed sectorial representation of energy demand</li> <li>- realistic projections</li> <li>- local demand representation</li> </ul>	<ul style="list-style-type: none"> <li>- identification of the relationship between economic variable and aggregate demand</li> <li>- reliance on aggregate data easy to obtain</li> <li>- reliability on historical trends able to drive the model</li> </ul>
<b>Weakness</b>	<ul style="list-style-type: none"> <li>- huge data deficiency especially for DCs</li> <li>- not able to capture price-based policy and price signals</li> </ul>	<ul style="list-style-type: none"> <li>- inability to capture technological diversity and technical progress</li> </ul>

617

618

619 Especially in rural areas, energy access planning should firstly consider the structural change in the  
 620 socio-economic dynamics caused by the introduction of new energy technologies, such as the  
 621 leapfrogging of economies (*e.g.* new income generating activities and opportunities) [108,109].  
 622 Secondly, an appropriate model for demand forecasting in rural areas must account for the demand  
 623 for end-use appliances [115]. This in turn depends on acceptability, deeply-rooted consumer  
 624 behaviours, social networks-based diffusion mechanisms, affordability, elasticity of the demand and  
 625 the inertia of the stock of available appliances. This is why Swan et al. [111] state that bottom-up end-  
 626 use approaches are more suitable for contexts where there is a rapid technological development as in  
 627 DCs. Ruijven et al. [114] and Daioglou et al. [115] integrated some of the typical features of energy  
 628 systems in DCs mentioned by Urban et al. [129] in their Residential Energy Global Model (REGM).  
 629 The model is able to capture many of the specific dynamics of DCs (*viz.* underdeveloped markets and  
 630 informal activities, the transition from traditional to commercial fuels, the role of income distribution and  
 the urban/rural difference). It also adopts deterministic correlations derived from econometric studies



631 and regression analysis on national data to project the energy use of households: this results a  
632 function of exogenous factors and drivers such as population, household size, household expenditures  
633 and temperature [130,131]. The use of such approaches for local applications might be prevented by  
634 the lack of local long-term data, as frequently happens in rural areas. In this context, the need to move  
635 towards mathematical approaches and instruments able to capture both the technical and the socio-  
636 economic-related dimensions of energy demand evolution emerges, as we summarise and propose in  
637 Table 2. As Khandker et al. [132] state, “the dynamics of growth and electrification are complex,  
638 involving many underlying forces” (p. 666) and feedback mechanisms: rural electrification is expected  
639 to positively impact new economic and educational opportunities, which in turn might make electricity  
640 and appliances more affordable, increasing the local electricity demand.

641 **Table 2.** Socio-economic- and energy-related dimensions of energy demand evolution in rural contexts

---

**Economic dimension**

- Considering the informal activities/economies that may bias available aggregate data on income [129]
- Considering income distribution and inequity among users, who may behave differently among different socio-economic classes [129]
- Modelling the new income generating activities and possibilities driven by more reliable access to energy [108,109]

**Social dimension**

- Modelling the urban and rural demand separately, since people have different needs and constraints [129][114]
- Considering also non-monetary factors that may influence the users, such as past experience, social norms, and trust-based information and perceptions of quality, satisfaction and social network [133][134][135][9]

**Energy dimension**

- Modelling the demand for end-use appliances following a bottom-up approach [115].
  - Considering the “user choice” of fuels and transition from traditional to modern energies, and vice-versa [129], especially for energy for cooking [136]
- 

642 To this end, SD seems an appropriate candidate tool, given its ability to represent complex socio-  
643 economic, techno-economic and socio-technical nexus causalities. Hartvigsson [9,112] highlights how  
644 SD can be a valuable methodological approach to capture the dynamics behind the evolution of  
645 energy demand in developing contexts, since the latter are affected by high uncertainty, strong non-  
646 linear phenomena, complex diffusion mechanisms, time-adjustments of technology perceptions [137].  
647 SD models have some limitations in modelling the social interactions that ensue within social networks  
648 and impact on consumers’ energy behaviours, since individuals are assumed to be always well-mixed  
649 and in many cases the interactions between compartments are assumed to occur at random [138]. Rai  
650 and Henry [134] indicate therefore that “agent-based modelling (ABM) is a powerful tool for  
651 representing the complexities of energy demand, such as social interactions and spatial constraints”  
652 (p. 1). As already stated by other studies in different research fields [139–142], we therefore conclude  
653 that coupling ABM and SD may be useful also to investigate in a comprehensive way the multi-faceted  
654 complexities behind energy choices and uses in rural areas.  
655

656 **Conclusions**

657 In developing contexts, the number of people affected by lack of reliable and affordable energy  
658 sources may be only slightly reduced in the incoming decades in spite of the many efforts and  
659 investments in the sector [5]. A number of studies was carried out on long-term rural energy planning  
660 since around the ‘80s, but the different foci, terminology and methodologies make it difficult to track  
661 the similarities, weaknesses and strengths of these works. Moreover, the aspect of energy demand is

662 far from being carefully addressed and analysed in rural energy plans. This in turn can constitute a  
663 barrier for researchers to build on the whole experience and findings of the authors. Indeed, most of  
664 the studies and the reviews focus only on the “supply” aspect of the rural energy planning.  
665 Coming from a modelling background and being interested in the prompt applicability of the existing  
666 know-how on long-term rural energy planning, we aimed at providing a critical analysis of the literature  
667 on the topic. The specific objective of the review is to provide a synthesis of strengths and  
668 weaknesses and fields of applicability of the approaches used so far, as well as the main modelling  
669 insights that can be derived from their applications.

670 The work resulted in the analysis of 126 studies and categorisation of 84 of them, under a number of  
671 rules clearly defined in the first part of the paper: (i) the implemented energy planning must be aimed  
672 at selecting energy conversion technologies able to match a certain demand with certain energy  
673 resources in an optimal manner; (ii) studies refer to real-life cases or potential applications for real  
674 contexts; (iii) only local rural energy planning for DCs (and BRICS) is considered, excluding works  
675 referring to other contexts or to global and national scales; (iv) in case of electricity planning, all the  
676 on- and off-main grid electrification options (standalone systems, microgrids and distributed hybrid  
677 microgrids) presented by the case studies are considered; (v) the papers must come from the  
678 scientific peer-reviewed literature, without any constraint on the publication period. These rules are  
679 meant to indicate the scientific ground of the analysis and to provide a benchmark to replicate and  
680 extend it.

681 As a novelty, we combined the analysis of both the “demand” and the “supply” aspects of the rural  
682 energy planning studies, stressing the need to consider and model these two parts of the planning as  
683 linked and interdependent. For this purpose, the studies have been classified in two ways:

- 684 i. Firstly, in accordance with their type: subcategories of spatial coverage, planning horizon,  
685 energy vector, decision criteria mathematical models and energy uses were identified and the  
686 studies classified under each of them;
- 687 ii. Secondly, in accordance with the methodology they employ to forecast the evolution of the  
688 energy demand, if any.

689 We came to the conclusion of performing such multi-layer categorisation based on the observation  
690 that the diversity of the studies spans over multiple dimensions and that selecting only few categories  
691 would have been simplistic and inconclusive.

692 From our classification, it emerges that about three quarters of the cases analysed refer to local rural  
693 planning (i.e. a village, a community, a group of small villages or a set of houses located in the same  
694 region of the same nation) and about two thirds carry out a long-term energy planning analysis (i.e.  
695 beyond fifteen years). Nevertheless, we found several case studies that did not report enough  
696 information for assessing the spatial coverage and planning horizon, preventing the findings to be  
697 extended to other similar cases of energy planning in analogous contexts. Electricity is found to be the  
698 most considered energy vector (79.0 % of the studies), followed by thermal energy (17.2%) and oil  
699 products (3.8%). The results reveal the need to increase the energy planning-based research on the  
700 other energy vectors, especially regarding thermal energy for cooking, given its priority in the  
701 Sustainable Energy for All (SE4All) global Agenda. Household end-use of energy is considered by  
702 most of the case studies, followed by communitarian, agricultural and industrial uses. Regarding the  
703 modelling approaches adopted to develop the planning, LP and EO result to be the most used,  
704 respectively by 27.9% and 33.7% of the reviewed studies. However, considering the multifaceted  
705 issue of sustainable rural energy planning – which includes important socio-economic and  
706 environmental aspects such as acceptability, technology appropriateness, indoor air pollution, local  
707 know-how and capabilities –, we suggest to enhance the research on MCDM and MOP models for  
708 more comprehensive energy planning studies.

709 Interesting conclusions emerge particularly from the analysis of the methodologies to forecast the  
710 energy demand. Few studies assume a dynamic demand over the years and most of them forecast its  
711 evolution through arbitrary trends and scenarios. This, however, undermines the relevance of the  
712 results for the purpose of long-term planning, as also remarked by [109]. We therefore encourage

713 future researches to pay more attention to this topic and consider carefully the importance of energy  
714 demand evolutions within rural energy planning studies, as inferred from [10–12]. We finally highlight  
715 the necessity of further developing the forecasting methodologies. To this end, we attempt to highlight  
716 the main socio-economic aspects that should be considered when modelling the evolution of rural  
717 energy demand: informal activities/economies, income distribution and inequity among users, new  
718 income generating activities and possibilities, difference between urban and rural demand, non-  
719 monetary factors such as past experience, perceptions of quality, satisfaction and social network, end-  
720 use energy consumption of appliances, user's choice of fuels and transition from traditional to modern  
721 energies. In this context, bottom-up approaches and system-dynamics seem potential appropriate  
722 approaches to tackle the context-specific complexities of rural areas, the nexus causalities among  
723 energy and socio-economic aspects, as well as the possibility to deal with high uncertainties and data  
724 scarcity. Such conclusion sets a starting point for our modelling work on enhanced demand  
725 forecasting methodologies and it is meant to contribute to the same effort of other researchers.

## 726 **Acronyms – Subscripts**

727	AHP	Analytic Hierarchic Process
728	AMPL	A Mathematical Programming Language
729	BRICS	Brazil, Russia, India, China and South Africa
730	CIA	Central Intelligence Agency
731	CP	Compromise Programming
732	DC	Developing Country
733	DP	Dynamic Programming
734	ELECTRE	Elimination and Choice Expressing Reality
735	EO	Enumerative Optimisation
736	ESMAP	Energy Sector Management Assistance Program
737	GP	Goal Programming
738	IEA	International Energy Agency
739	IREOM	Integrated Renewable Energy Optimization Model
740	IRES	Integrated Renewable Energy System
741	LCOE	Levelized Cost of Energy
742	LP	Linear Programming
743	MCDM	Multi-Criteria Decision Making
744	MOP	Multi-Objective Programming
745	NLP	Non- Linear Programming
746	OECD	Organisation for Economic Co-operation and Development
747	PV	Photovoltaic
748	REMG	Residential Energy Model Global
749	RET	Renewable Energy Technology
750	SD	System Dynamics
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