Critical review of energy planning models for the sustainable development at company level

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Review

Critical review of energy planning models for the sustainable development at company level

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ABSTRACT

Companies in the manufacturing, service and transport infrastructure sectors will play a key role in the sustainable transition of the energy system implementing innovative technologies at full industrial scale. However, developing long-term investment plans is a challenging task, complicated by the volatility of energy markets and the uncertainties induced in the policy landscape by the recent energy crises. In this respect, mathematical models can support the transition of industrial systems, steering the planning process. In this work, we review and evaluate the suitability of available models to serve this purpose. The availability of modelling tools for local energy planning has already been assessed by several works. However, the tools which are most frequently employed at this scale are generally unable to characterise the evolution of the energy system in the long term, they have a focus on the operational aspects of the system, and are, in many cases, proprietary. By contrast, all the models examined in this review are open source, and the investigated set also features tools able to capture long-term dynamics. Our results provide evidence that several tools could offer valuable insights to the planning process. Nevertheless, a trade-off between the representation of long-term dynamics and the modelling of key aspects of the energy system of a company is, to date, inevitable. The best compromise is offered by a small group of multi-scale tools, able to conjugate a long-term perspective with a detailed modelling of the operational aspects of the system.

1. Introduction

The 26th Conference of the Party held in 2021 in Glasgow (COP26) witnessed an unprecedented participation of the private sector. After the release of the Sixth Assessment Report of the IPCC, it has become clear that the joint effort of the public and private sectors is needed to keep global temperature from rising above 1.5 °C. As the engagement of businesses increases, it is expected that more and more companies will have to commit to net-zero emission targets in the near future [1]. While this is already a reality in the UK, where listed companies will have to publish their net-zero strategies by 2023 [2], the call for the development of Corporate Determined Contributions made by the WBCSD at COP26 also points in this direction [3].

One key action companies can take to directly reduce their carbon footprint is revisiting the way they source and produce energy. Albeit energy is fundamental for any commercial activity, its related emissions make up the lion's share of the carbon budget of most businesses. Investing in on-site or off-site renewable generation and energy efficiency projects, switching to renewable or low-carbon fuels, purchasing green electricity from the market, are among the viable options to improve the environmental sustainability of a company. However, the radical transformation of the energy system can be a challenging task for an enterprise. Many external factors, like the sustained increase of the costs of fossil fuels and electricity, the volatility of power and carbon price, as well as the unprecedented deployment of new technologies, call for the establishment of a robust planning methodology. In this perspective, it is essential to provide companies with the appropriate tools to develop their energy strategies. These tools should be able to conjugate a long-term vision [4] with the impellent necessities dictated by the recent energy crises.

Energy System Models (ESM) could provide the necessary analytical tools to manage complexity [5]. ESM have a long history in supporting decision-making at national and international level [6–8]. Though their focus remains on large-scale systems [9], their application to local energy planning has received growing attention over the last two decades [10,11]. The definition of local or Distributed Energy System (DES) encompasses a wide range of spatial scales: from a single building or factory, to an urban district, up to entire cities and regions [12]. Given their scope, DES models could be suited for the analysis of the facilities

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Abbreviations

COP26	The 26th Conference Of the Parties
DES	Distributed Energy System
DSM	Demand Side Management
ESM	Energy System Model
ETS	Emission Trading Scheme
GHG	Greenhouse Gas
GUI	Graphical User Interface
IDS	Investment Decision Support
IPCC	Intergovernmental Panel on Climate Change
MES	Multi-Energy System
MILP	Mixed-Integer Linear Programming
ODS	Operation Decision Support
openmod	Open Energy Modelling Initiative
PSAT	Power System Analysis Tool
PtG	Power-to-Gas
PtH	Power-to-Heat
TSA	Time Series Aggregation
WBCSD	World Business Council for Sustainable Development

of companies in a wide range of sizes.

A significant effort has been dedicated to developing new models and techniques to address the design of DES [13], and a large number of studies [14–17] have addressed the availability of modelling tools. However, the analysis of relevant review works conducted in this paper revealed that, despite the vast panorama of available models, most of the tools proposed for the analysis of DES still present some weaknesses. First, they prevalently focus on the operational aspects of the energy system, rather than on the optimisation of economic decisions. This makes them less suitable for the development of an energy strategy. Moreover, they are generally unable to capture long-term dynamics in the design of the system [18]. Conversely, large-scale models are commonly used for planning several decades in the future. For this reason, it has occasionally been proposed that tools initially conceived for larger scales could be adapted to smaller scales [19]. Nonetheless, a quantitative and exhaustive comparison of large- and small-scale models has yet not been conducted. Finally, it was noted that the proposed models are prevalently academic or commercial, while only a minority is available free-of-charge or under an open-source license.

Taking into consideration the gaps identified in literature, this paper aims at evaluating the suitability of open-source ESM to support companies in the development of a long-term investment plan. The term *companies* encompasses a wide range of businesses. In this paper, we specially focus on those companies belonging to the manufacturing, service, and transport infrastructure sectors, although the results could be generalised to other types of businesses. The evaluation of ESM models is conducted as follows: first, a set of features required to model the energy system at company-level is determined; then, a selection of models is carried out and their ability to fulfil these requirements is assessed. Both DES and large-scale models are included in the analysis. A detailed and quantitative comparison of their modelling capabilities is provided, assessing the availability of more than 100 specific modelling functions.

The paper is organised as follows. Section 2 summarises the results of the relevant review works in the field of ESM. Section 3 illustrates the methods used for the selection and evaluation of the modelling tools. Section 4 presents the criteria used to evaluate the tools. Sections 5 and 6 report and discuss the results of the analysis. Finally, section 7 concludes the paper.

2. Survey of review works on energy system models

The application of mathematical models in support of energy planning is not a widespread practice in private companies [5], so the available literature on this topic is limited. Among the reasons for their limited diffusion in this field, it is remarked that the need for long-term energy planning has been just recently prompted by growing concerns around climate change. From a spatial standpoint, the facilities of a company span various sizes: from a single building, like a shopping centre or a factory, to clusters of buildings, like campuses and industrial parks, and even larger business agglomerates. Airports are exemplary cases, whose size can vary from few buildings [20], up to actual metropolis [21]. Fig. 1 offers a visual comparison of the size of various types of companies, compared to a scale to which Energy System Models (ESM) are commonly classified. Distributed Energy System (DES) models have been applied to energy systems whose size and characteristics are like those of many types of companies. Therefore, the existing literature on DES can be taken as the starting point for analysing the problem of energy system planning in companies.

A wide array of ESM exists: as of 2023, the website of the Open Energy Modelling Initiative (openmod) lists more than 80 modelling tools [22]. Many of these tools present similar functionalities [23], while their main area of application is not always explicitly reported in literature [24]. Choosing among an increasing number of slightly different tools can be complex [25]. This considered, review works provide an important resource to support modellers in the selection of a tool suitable for their research question [26]. In this section, a survey of the works investigating the suitability of ESM for the design of DES is presented. The aim of this analysis is to identify which modelling tools are commonly applied to the design of DES, and which are the prevalent methodologies used in this modelling field.

Connolly et al. [27] reviewed and compared 37 computer tools, aiming at identifying suitable frameworks for modelling energy systems with high penetration of renewable generation. The scale of the models examined ranged from a single building to national energy systems. In this work, only four tools were found to have a focus on the integration of renewable energy at building and local levels. More recently, Ringkjøb et al. [28] compiled an extensive review of 75 modelling tools, with the similar goal to provide an overview of the available frameworks to model electricity systems with high shares of renewables.

Other reviews works target more specifically the design of DES [10,16,17,29–36]. The latter often appear in literature under the denomination of local or community energy systems. Nakata [30] and Hiremath et al. [37] are two early works reviewing the application of ESM for DES planning. Their focus was restricted to rural areas, urban districts, and regions. Both Markovic et al. [16] and Mendes et al. [17] conducted a survey of software tools to support various aspects of planning community energy systems. Among the ESM, they listed *HOMER*, *DER-CAM* and *EnergyPLAN*. Mendes et al. also proposed that *MARKAL/TIMES* could be adapted to analyse the long-term deployment of distributed generation, due to its scale-flexibility. Lyden et al. [33] developed a step-wise, quantitative selection process to identify suitable tools for planning community energy systems. Among the 51 tools initially considered, *COMPOSE*, *DER-CAM* and *energyPro* achieved the highest scores. Weinand et al. [10] reviewed 123 studies on the modelling of autonomous energy systems at the local scale. They found out that the simulation approach was prevalently adopted in these studies, and that *HOMER* was by far the most employed tool. Sinha et al. [36] described 19 software tools for the design of hybrid renewable energy systems, concluding that *HOMER* was the most widely used. Similarly, Fathima et al. [29] listed several software tools available for the optimisation of hybrid micro-grids, but also included large-scale models such as *Balmorel* and *MARKAL/TIMES*.

Many other reviews focus, instead, on a sub-scale of DES. For instance, Thiem [38] reviewed 11 tools for the optimal design of small-scale energy systems, like airports and campuses. Timmerman

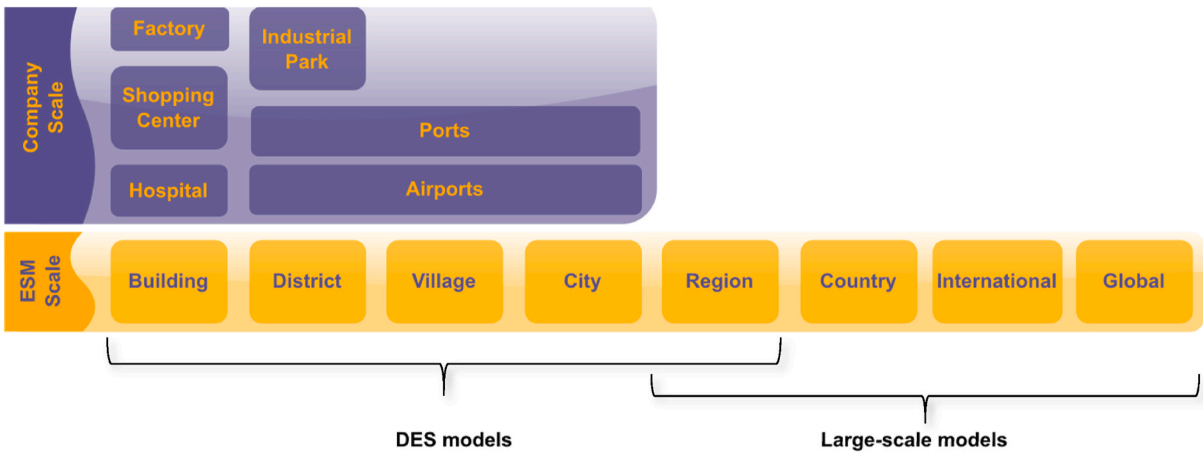

Fig. 1. Visualisation of the spatial coverage of ESM designed for large-scale and DES, and overlap with the facilities of companies of various sizes.

et al. [19] denounced a lack of tools specifically tailored for industrial park energy systems. To fill this gap, they proposed to adapt large-scale tools like *OSeMOSYS* and *TIMES* to determine the optimal evolution pathways of industrial energy systems. The works of Allegrini et al. [15], Doubleday et al. [39] and Olsthoorn et al. [40] all focused on the planning of district energy systems. Finally, the field of urban energy planning is gaining a significant momentum, and several works have attempted to identify suitable tools for modelling energy systems at this scale [14,41–46]. The paper of Van Beuzekom et al. [14] is particularly relevant in this field. Among the 13 tools considered in this review, large-scale models like *TIMES* and *Balmorel* are juxtaposed to small-scale ones like *HOMER* and *DER-CAM*.

An analysis of the frequency with which the various tools appear in the reviews allows to derive some interesting insights on how the problem of DES planning is commonly addressed in literature. In the 22 reviews taken into consideration, 118 modelling tools have been proposed. These range from building simulation tools like *EnergyPlus*, to techno-economic models for the optimal sizing and operation of the system like *DER-CAM*. Fig. 2 shows the number of occurrences of the tools most frequently cited in the reviews. Unsurprisingly, *HOMER* is by far the most cited tool, almost omnipresent in the examined reviews, which is a recognition of its widespread application [10]. Interestingly, tools like *LEAP*, *MARKAL* and *TIMES* find a place among the ten most cited tools. This suggests that the adaptation of large-scale models to DES is frequently proposed in literature. Looking at the methodology employed by the first six tools, *DER-CAM* stands out as the only investment optimisation framework[1].

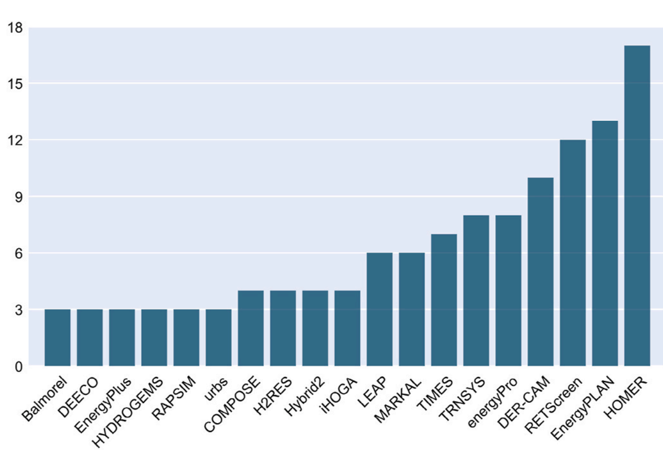

Fig. 2. Number of occurrences of the modelling tools in the examined reviews.

Fig. 3 a provides further insights on the methodological approach of the tools across the whole dataset. Apparently, a majority of tools is based on a simulation strategy or focuses on the optimisation of the operation and scheduling of the system. This underpins that DES models pay a significant attention to the operative facets of the energy system.

A comparatively smaller share of tools focuses on the optimisation of investment decisions. The vast majority of these only performs a static optimisation of the energy system. This means that investment decisions are optimised for a single or few years, which are taken as representative for the whole investment period [18,47]. An even smaller number of tools can perform investment decisions for multiple investment cycles, spanning a longer time horizon. These tools enable the study of the evolution of the system. Specifically, *COMET*, *MODEST* and *eTransport* are the only tools explicitly designed for DES which can characterise the evolution of the energy system with a multi-year approach. However, none of these tools is freely available for public use, to the best knowledge of the authors. The lack of DES modelling tools able to perform multi-year investment optimisation was already observed by Mavromatidis et al. [18]. Despite some models supporting this functionality have been developed [18,48,49], they have yet not been made available to the public.

Comprehensibly, the problem of characterising the optimal evolution pathways of DES is usually addressed by resolving to large-scale modelling tools, as shown in the top-right corner of Fig. 3a. However, it is often argued that large-scale models cannot provide precise information to the design of DES. This either because of their allegedly aggregated view of the energy system [18] or because of the oversimplification in the representation of the operational aspects [12]. Although the work of Cuisinier et al. [12] provides an excellent methodological comparison of local and large-scale models, an extensive assessment of the capability of large-scale tools to model DES has yet not been conducted.

One last observation can be made about the availability of modelling

[1] *HOMER*, *EnergyPLAN* and *energyPRO* are frequently classified in literature as optimisation tools [16,27,41]. Even though all these frameworks include an optimisation module, their underlying methodology is simulative [72,161,162]. To adhere to a strict formal classification of the tools, they have been considered simulation tools in this paper.

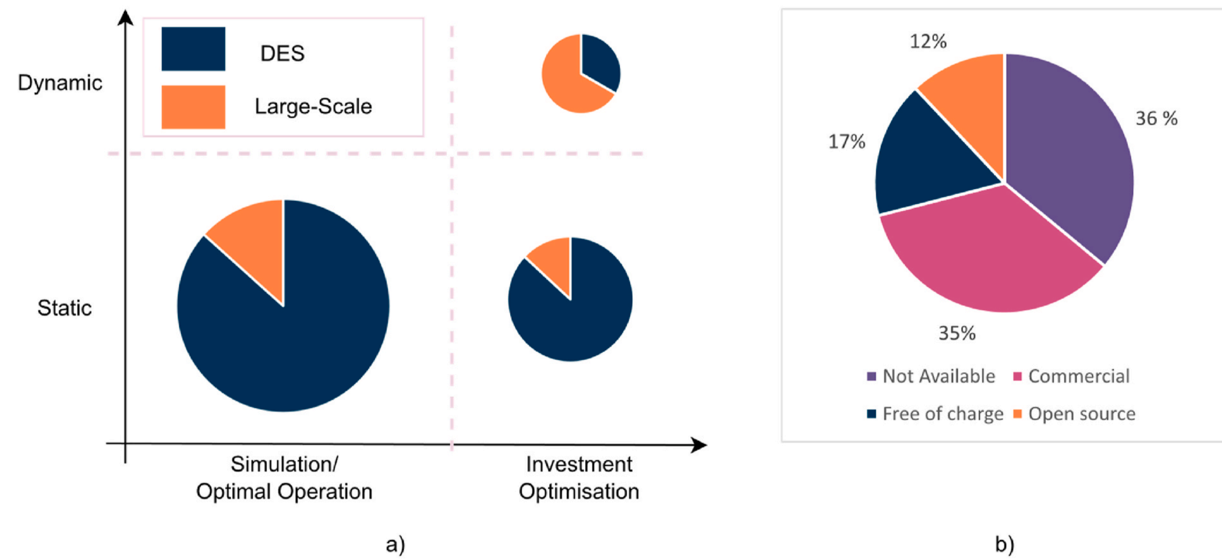

Fig. 3. a) Methodology and b) availability of DES tools reviewed in previous works.

tools designed for DES. Fig. 3.b shows that 35% of the reviewed tools are commercial, while an almost equal share is not available for public use, being proprietary software used for internal purposes. Even though some tools can be downloaded at no cost, only 12% of them is open-source.

In summary, based on our analysis of the several reviews on DES modelling tools, three gaps were clearly evidenced:

1. First, most of the proposed tools employs a simulation approach, focusing on the operation of the system rather than on the optimisation of investment decisions.
2. Second, very few DES tools are suitable for assessing the optimal evolution pathways of the energy system. Even though large-scale tools are frequently proposed to address this issue, a detailed comparison of large- and small-scale tools is currently missing in literature.
3. Third, most of the reviewed tools are not freely available, being either commercial or developed by institutions for internal use.

3. Methods

This paper provides a detailed and quantitative evaluation of the capability of state-of-the-art ESM tools to support the development of an investment strategy at company-level. The thorough comparison of models conducted in this study aims at guiding the modellers in the selection of the tool most suited to their specific application. This section describes the methods used for the inclusion of the models in the review and for their evaluation, alongside the inherent limitations of the applied methodology.

While numerous reviews have assumed a holistic perspective of energy planning [15,17], this work focuses on a sub-class of energy system models, in the attempt to fill the gaps identified in the analysis of existing literature (cf. Section 2). In this context, only open-source tools able to optimise investment decisions were examined. In addition, large-scale models able to perform multi-stage investment optimisation were included in the analysis, and thoroughly compared with tools explicitly designed for DES.

Several reasons underpin these choices. First, open-source tools are publicly available and present a lower financial barrier with respect to their commercial counterpart. This makes them readily and economically accessible for use in companies of any size. Second, even though also simulation tools can provide useful insights to the planning task [50], they usually have a focus on the operational aspects of the system. Comparatively, investment optimisation models are more suitable for supporting long-term investment decisions [26]. Finally, most of the tools designed for DES planning implement a static approach, hence they are not able to consider long-term dynamics. Neglecting these dynamics can lead to the underestimation of system costs and sub-optimal investment decisions [49,51]. This holds especially true if the continuous evolution of the energy market and policy framework is considered. Therefore, large-scale tools were included in the analysis.

The tools were evaluated following the scheme presented in Fig. 4. The vast landscape of modelling tools was initially screened to filter the candidates responding to the criteria outlined in Fig. 5. The set of criteria adopted was intentionally designed to be highly selective, so to ensure that the tools participating in this survey shared common working principles. In this way, the detailed and equable comparison of their functionalities can be ensured. The database hosted by openmod [22] was used as the starting point of the search. Of the 83 tools listed on the website, only 13 passed our screening phase. The *FINE* [52], *GENeSYS-MOD* [51] and *SpineOpt* [53] models were not present on the openmod website, but they all respected the screening criteria and were then added to the set. Finally, *DER-CAM* [54] was added to the investigated set to provide a comparison with a closed-source framework. *DER-CAM* has been internally developed and maintained by researchers at Lawrence Berkeley National Laboratory, and it is released free-of-charge as an executable application. It was selected as reference since it is a mature and widely adopted tool in the field of *DES* optimisation, as testified by the hundreds of scientific publications using it[2]. Moreover, although closed-source, the clear and detailed documentation provided offers a sufficient level of transparency to allow the comparison of its functionalities with open-source tools.

It is underlined that the panorama of ESM is wide and fast changing, with new tools being released each year. For this reason, despite the thorough search of literature conducted by the authors, it is possible that some tools possessing the required criteria had been left out of the investigated set.

As next step, the 17 tools selected were classified according to their purpose, implementation, and technical features. It is worth noticing that several attempts have been made to categorise ESM [55–58]. Nevertheless, a definitive classification scheme has not yet been conceived. In this work, the classification introduced by Ringkjøb et al.

[2] Follow this link for a full list of publications using *DER-CAM* https://gridintegration.lbl.gov/publications?page=0.

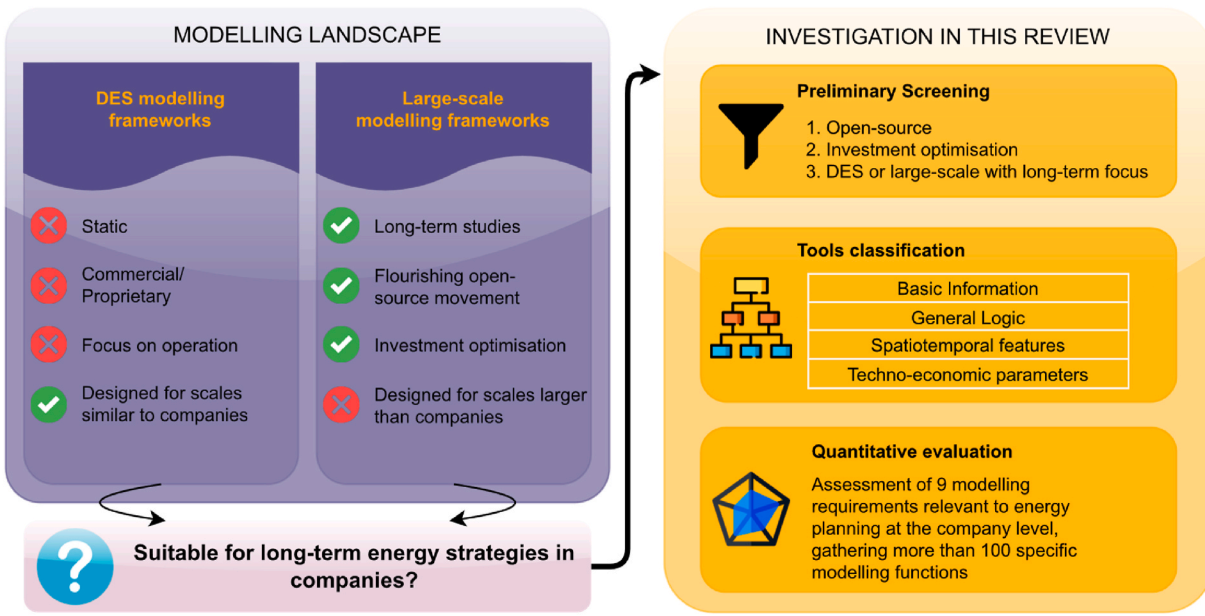

Fig. 4. Scope of the review and steps of the evaluation scheme.

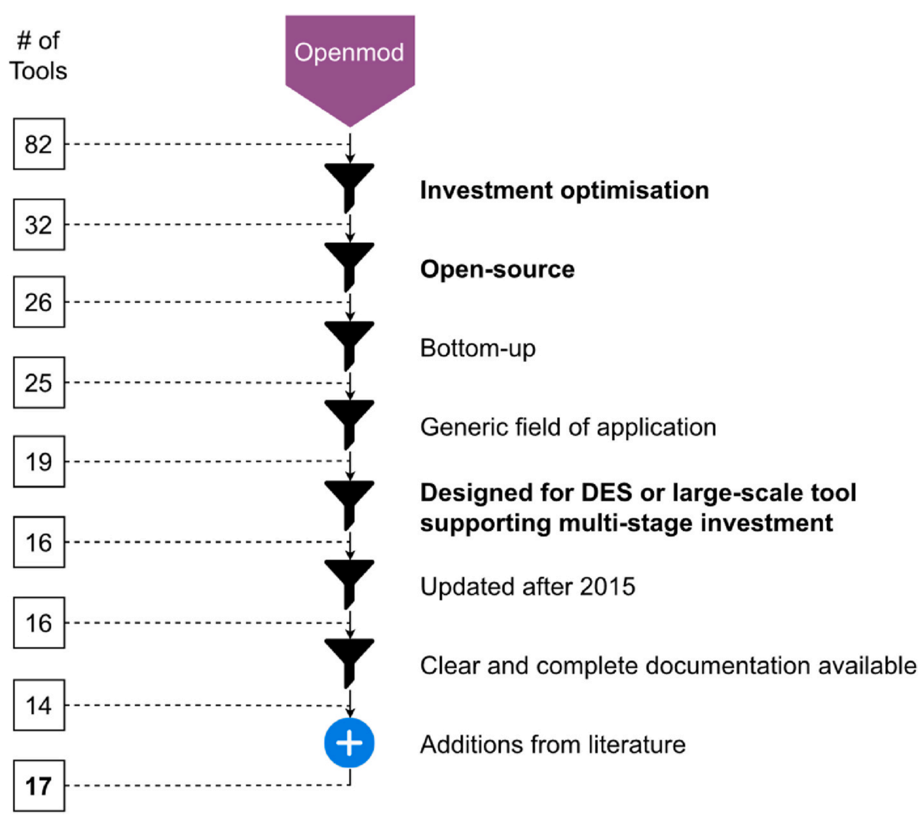

Fig. 5. Preliminary screening of the modelling frameworks. The figures on the left show the number of tools which were selected at each screening stage.

[28] was chosen, because of its completeness and the relevance to the topic. The structure of the classification scheme is reported in Fig. 6. The categories proposed by Ringkjøb et al. were occasionally expanded to consider additional criteria that could prove useful in the selection process.

It has occasionally been observed that papers comparing energy models offer little insights on the modelling capabilities of the tools [59]. Comprehensively, recent reviews have incorporated more detailed criteria, specifically related to the modelling capabilities of the tools [60–62]. In this work, in addition to the classification scheme, the selected modelling tools were compared based upon their capability to fulfil nine modelling requirements. These requirements, widely presented and discussed in Section 4, were deemed necessary to model an

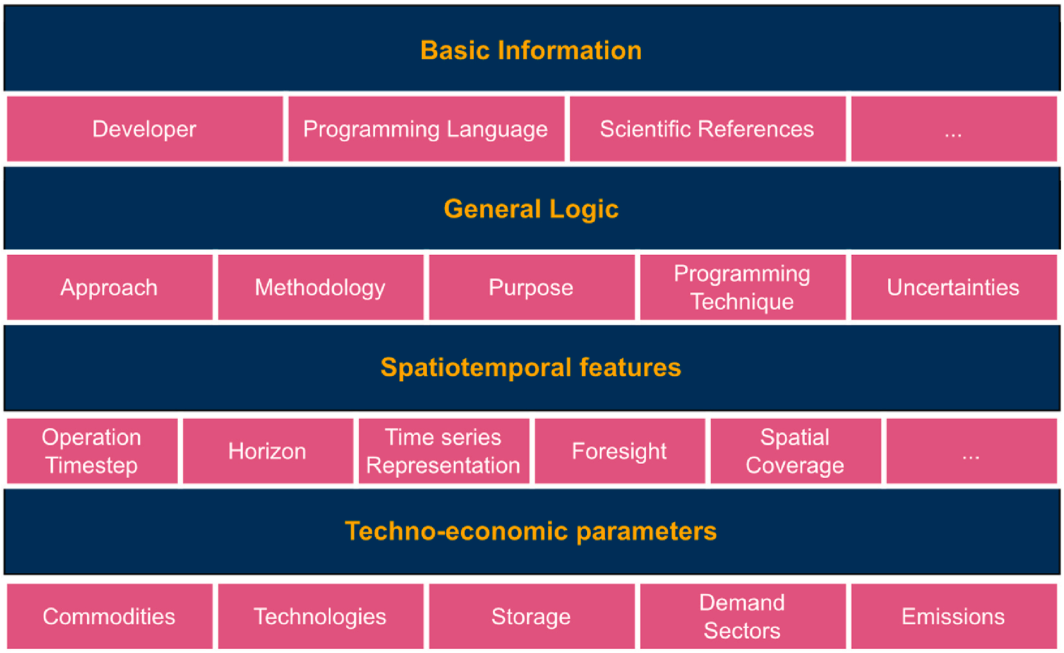

Fig. 6. Structure of the classification scheme proposed by Ringkjøb et al. (Adapted from Ref. [28]).

energy system at company-scale. They were derived from a literature review and from the experience maturated during the project which supported this study[3]. They range from the ability to represent the operation of the system, to the usability of the tool.

While more thorough methods exist for comparing ESM, such as the benchmarking of the models on a harmonised energy system and scenario[4], it can be argued that following such an approach to compare 17 tools would be impracticable. Nevertheless, we believe that the level of detail achieved by this review can provide a first selection of most performing models, which could be further investigated in a future work.

For each modelling requirement, a set of specific modelling functions was identified. The total number of functions investigated adds up to more than 100. The ability of a tool to fulfil a modelling requirement was then quantitatively evaluated. Each modelling requirement, here identified with the subscript i, was assigned a set of functions (subscript f). The availability of the function (a_f) was then assessed through a detailed review of the documentation and the source code of the models. A value of 1 was assigned to a_f if the function was fully supported; half a point if the function was partially supported; 0 if the function was completely absent or if it was not possible to determine its availability. The performance parameter of a model in each dimension is expressed by the equation:

$$P_i = \frac{\sum_{f \subset P_i} a_f}{N_i}$$

Where N_i is the number of functions in the i dimension, and P_i the performance parameter comprised between 0, if none of the functions is supported, and 1, if the totality of the functions is available in the modelling framework. It was preferred not to use a weighting scheme to evaluate the overall performance of the tools. This because the coefficients used to weight the single functions or modelling requirements might vary from company to company. However, the tables provided in the Supplementary Material enable modellers to recompute the performance parameter, applying a weighting scheme compatible with their research questions.

A specific attention was devoted to ensuring the accuracy of the presented data. The review was based on high-quality material, including the code and documentation of the tools, and their associated scientific references. However, Chang et al. [11] observed that modelling tools can be potentially misrepresented if no dialogue with the developers takes place in the review process. To address this problem, personal communications with the developers were established when uncertainties emerged around the characteristics of the tool. Nonetheless, it should be considered that the information reported in this paper about the characteristics of the tools was not fully reviewed by the respective developers.

4. Modelling requirements for a company-level energy system

This section introduces the modelling features required to perform reliable investment planning studies for an energy system at the company-level. As extensively described in Section 3, these features were used to evaluate the applicability of the models to the problem under investigation. Nine modelling requirements were identified. Eight of them are technical ones, like the ability to include operational features in planning models or to represent flexibility options, while the last addresses the usability of the tool. Table 1 summarises the main results of the review, presenting and defining the modelling requirements, as well as part of the associated modelling functions. A full list of the modelling functions used for the evaluation of the tools is available in the Supplementary Material. Each of the requirements, their relevance for energy system planning in companies and the related modelling functions, are shortly described in the following sub-sections.

4.1. System operation

The operation of the system is intended as the ability to reproduce the real behaviour and technical constraints of the energy conversion and generation technologies. Operational aspects are addressed with various levels of detail by ESM. Traditionally, investment optimisation models tend to simplify the operational part of the system, in order to

[3] TULIPS project, https://tulips-greenairports.eu/.

[4] https://www.sciencedirect.com/journal/renewable-and-sustainable-energy-reviews/special-issue/107488GHL69.

Table 1
Modelling requirements required to conduct energy planning in companies, and associated modelling functions.

Modelling Requirements	Definition	Modelling Functions
System Operation	The ability to represent operational constraints in investment planning models	Hourly time-step; flexible temporal structure; time series aggregation techniques; ramping constraints; time-dependent efficiency; part-load efficiency; minimum operational level; …
Flexibility Options	The ability to represent flexibility options, like storage and DSM	Constraint on charge/discharge of storage; constraints on storage level; storage self-discharge; storage degradation; constraint on storage cycling; load curtailment and load shifting; …
Transactive Market	The possibility to model the participation in the electricity market	Simple charge tariffs; fixed-charge tariffs; peak-demand tariffs; tiered electricity prices; …
Multi-Energy System	The representation of multiple energy vectors and sector-coupling options	Representation of multiple demand sectors; generic definition of technologies and storage; MIMO technologies; fuel-switching capabilities; …
Energy Networks	The detailed representation of energy networks and their physics	Connection efficiency; connection capacity; OPF; DCOPF; SCOPF; thermal networks; …
Energy Transition Pathways	The ability to capture long-term dynamics and to determine the evolution of the system	Multi-stage investment optimisation; perfect and/or limited foresight approach; year-dependent demand, year-dependent variable operation costs; year-dependent investment costs; year-dependent emission targets; …
Uncertainties Handling	The possibility to address uncertainties in a systematic mode	Routines to handle large number of scenarios for sensitivity analysis; Monte Carlo simulation; Stochastic Programming; Robust Programming; Modelling to Generate Alternatives; …
Targets	The possibility to set multiple targets and constraints	Emission reduction targets; Minimum shares of renewable/self- production; resources and land availability constraints; …
Usability	The accessibility and ease of use of the tool	Open-source; free-of-charge; GUI; building loads and weather database; clear documentation; online resources; …

reduce the computational time [34]. This is particularly true for long-term models, where the optimisation of the system over several decades entails a major computational burden. However, the over-simplification of the system operation can significantly affect the investment decisions, especially under scenarios with high penetration of fluctuating renewable generation [63,64]. This is in contrast with the attention which is commonly paid to the operational aspects of the system in the design of DES, as highlighted in Section 2. Therefore, a proper trade-off between the complexity of the system and the tractability of the model is required in order to conduct reliable investment studies [65].

Several works have investigated the different levels of detail with which the operational facets can be introduced in ESM [64–66]. The foremost requirement to accurately reproduce the behaviour of the system is the use of a high temporal resolution. This is necessary to capture the variability of intermittent renewable energy sources [67] and it was found to impact the results of the optimisation even more profoundly than operational constraints [63,68]. All in all, the take-home from the reviewed works is that a model should ideally support at least hourly operation time-step, which can be considered acceptable for application at local scale [12]. Moreover, those models which support techniques to reduce the computational burden, such as a flexible temporal structure (e.g., a variable operation time-step) and Time Series Aggregation (TSA) algorithms [69,70], offer the possibility to increase the temporal granularity, while maintaining the tractability of the model.

In addition to a high temporal resolution, the behaviour of the system can be more accurately modelled by introducing operational constraints. Several authors have investigated the inclusion of operational constraints in investment planning models, both at large [61,63,68] and local scales [12,64,71]. Prior research suggests that energy conversion processes can be modelled with different technological details [61]. On the lower end, technologies can be represented as fully flexible processes with constant efficiencies. The operation of the system can be more realistically described by introducing ramping constraints, start-up/shut-down time, part-load efficiency, and minimum part-load limitations. At present, it is not uncommon to consider in long-term investment planning models also the optimal scheduling of technologies [72]. Also in this case, numerical techniques to reduce the complexity of the model, inter alia rolling horizon and problem decomposition, may be needed [12,66] to maintain the tractability of the model.

4.2. Flexibility options

The transition toward a more sustainable energy system requires the deployment of large shares of renewable generation. Given the intermittent nature of such renewable energy sources, addressing the mismatch between power production and demand will be a pillar of future energy systems. Therefore, flexibility options are becoming an essential component of energy systems [73]. Storage technologies and Demand Side Management (DSM) are two widely considered options to decouple energy generation from consumption.

Therefore, ESM should be able to represent a variety of storage technologies, from short-term storage, like batteries and thermal tanks, to seasonal storage for hydrogen produced via electrolysis [13]. A realistic modelling of the operation of storage is essential to avoid overestimating or underestimating the system capability, especially in terms of flexibility [73,74]. A basic representation of storage should at least consider the state of charge, within an appropriate timescale, and charge/discharge efficiencies. More complex representations include the storage self-discharge and constraints on the charge/discharge rate and the storage level. Advanced modelling techniques consider specific physics of the storage, like thermal stratification in storage tanks [75], the ageing of batteries [76], or the interaction of the battery of electric vehicles with the grid [77].

The diffusion of the concept of smart-grids would favour the bi-directional flow of data between the utility and the consumer, opening to new flexibility options through DSM [78]. The control and scheduling of energy demand can be exploited to reduce the electricity consumption during peak hours, or to shift load from periods of low renewable generation to periods with high generation [13,79,80]. Therefore, models aimed at designing the future local energy systems should be able to integrate DSM strategies, such as load shifting [81].

4.3. Transactive Market

The interaction with the electricity network is another important form of flexibility for grid-connected energy systems. As private actors evolve from consumers to prosumers, the bi-directional exchange of electricity with the utility grid becomes an attractive option for the creation of new business models. On one side, utility grids can provide power to the company in times of low on-site production, while grid-connected private actors can sell surplus renewable electricity, generating revenue. In this way, the curtailment of renewable generation can be avoided, limiting at the same time the need for expensive storage technologies or DSM strategies.

Therefore, a key aspect for DES modelling is that the potential interactions between the company energy system and the grid has to be carefully depicted in investment planning models [12]. For instance, the type of electricity contract can significantly influence the investment decisions, and the incentives for distributed generation [5,82]. ESM should be able to represent different types of utility tariffs, from simple flat rate and fixed charge tariffs to more complex structures, considering the time of use, peak charges and electricity tiers [83,84]. Similarly, net metering agreements should be explicitly modelled, so to capture different structures for electricity pricing and exchange limits.

Even though not included in this review, it is worth mentioning that also the participation in other energy markets, such as ancillary service and district heating markets, could significantly impact the investment decisions of a company [85,86].

4.4. Multi-energy system

The energy needs of a company largely depends on the type of activities and processes conducted. In view of the growing phenomenon of electrification, the planning of the future electric system is central for many businesses. However, the interest of some companies, e.g. in the steel and cement industry, could lie in high-temperature processes, which are difficult to electrify. Other companies, such as those in the transport infrastructure sector, would require a more holistic view of the energy system. Thus, models should consider the thermal demand of their facilities, as well as the demand for the transport services offered to customers and employees. Therefore, the selection of a suitable model also passes through its ability to represent multiple energy carriers and system coupling options, depending on the research questions.

The interaction of multiple energy vectors represents an attractive opportunity to increase the performance of the system, in particular for distributed generation [87–89]. Cogeneration and trigeneration plants are typical solutions integrating different energy vectors, which are already widely adopted by many large consumers [90]. The possibility of using flexible Combined Heat and Power (CHP) units to balance variable renewable generation has also been explored by many authors [91–94]. Power-to-Heat (PtH) [95] and Power-to-Gas (PtG) technologies [96], alongside the management of the charging pattern of electric vehicles [97] are other examples of system coupling, which might provide further balancing options for renewable generation.

A pre-requisite for MES modelling is the ability to represent the demand of multiple energy sectors, such as electricity, heating, cooling and transport. The representation of MES also requires modelling a wide range of technologies, powered by different fuels and blends [98]. Modelling tools implementing a generic definition of technologies, rather than restricting the choice to a limited set of predefined generation units, provide the flexibility needed to model a wide variety of options [44]. Moreover, the possibility to model Multiple-Input-Multiple-Output (MIMO) technologies is frequently required for sector-coupling options, like CHP units [62]. The flexibility of MIMO technologies in producing different energy carriers should be carefully modelled since, as discussed by Helistö et al. [75], it can drastically affect system costs. Finally, fuel-switching capabilities are necessary to model the transition from fossil sources to more sustainable biomass-based and synthetic fuels [44,88].

4.5. Energy networks

Modelling energy networks may result superfluous for small energy systems, such as single buildings [12], but the accurate representation of energy flows is important for the planning and implementation of micro-grids [34], district heating and cooling [15] or the exchange of waste-heat in industrial parks [19].

Energy flows can be represented in energy system models with different granularity. In single-node models, energy networks are completely omitted. This assumption, also known as "*copperplate approach*", allows energy to flow unconstrained from any generation site to any consumption site. Conversely, in multi-node models the flow of energy between different nodes can be constrained. Geidl et al. [99] distinguished two ways to model network connections. In the more elementary way, networks are defined as generic connections characterised by an efficiency and a transmission capacity. More accurate representations of energy flows can be achieved incorporating constitutional physical laws, specific to the type of connection which is modelled.

The specific physics of electricity networks can be modelled considering power flows. In linear models, this is achieved considering a linear version of the Optimal Power Flow (OPF) problem [100]. The Direct Current (DC)OPF is the most common linearisation technique [101]. Another variant of the OPF is the Security Constrained (SC)OPF, which includes contingency constraints in the optimisation problem [100]. As concerns thermal networks, their specific physics can be included in optimisation models considering thermal losses and pumping requirements.

4.6. Energy transition pathways

The transition of a company towards more sustainable energy systems requires the development of an investment plan with a reasonably long-term view [4]. Representing the long-term dynamics of the energy system can prevent investments that could result in stranded assets or technology lock-in Ref. [49]. Examples of long-term dynamics are the recent increase in electricity and gas prices in Europe [102] and the drop in the cost of renewable energy generation in the last decade [103]. Therefore, ESM should be able to capture these dynamics and to provide guidance not only on the most convenient technologies to invest in, but also on the timing of the investment [18,49].

As regards the timescale of investment optimisation, ESM typically follows two approaches (Fig. 7): static and multi-stage (or dynamic) investment optimisation [47]. Static models usually optimise a single year in the future, assuming that this year is representative for the whole horizon. Conversely, multi-stage models optimise the energy system over a longer time horizon, making investment decisions for multiple, subsequent investment stages. A further distinction can be made for multi-stage models, based upon the level of foresight [104]. A perfect foresight model optimises the system assuming a perfect knowledge of future events, over the entire modelled horizon. On the contrary, the models with limited foresight optimise subsequently each investment stage, with limited information on the future evolution of the system. This may lead to suboptimal solutions, and potential higher costs of the system [105]. However, the myopic approach allows to contain the computational time [106,107], thus opening for a more detailed representation of the system, as discussed in Section 4.1. Moreover, it resembles more closely the way investment planning is usually conducted in reality [106], meaning that results can be more easily interpreted by stakeholders.

Independently from the level of foresight of the model, the multi-stage investment models present a clear advantage over static ones. Static models fall short in delivering insights on the long-term development of the system, and could provide sub-optimal solution by, for instance, neglecting the evolution of fuel prices and technology costs [49]. On the other hand, multi-stage models can characterise the evolution of the system, considering the variability of several parameters over the modelled horizon.

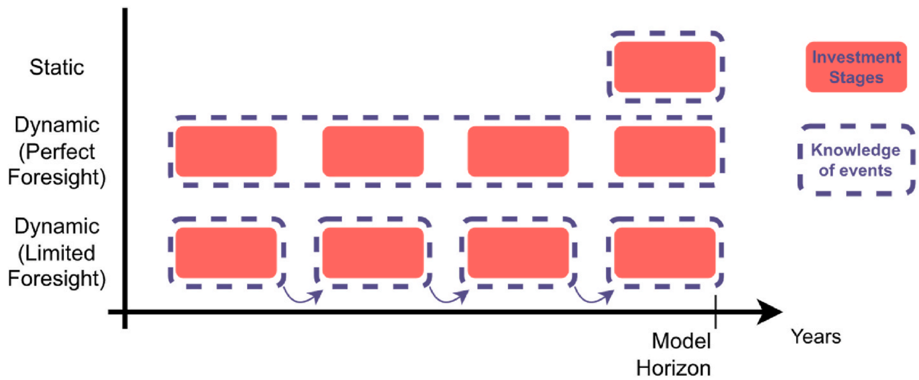

Fig. 7. Static and Dynamic approaches and conceptualization of different levels of foresight.

4.7. Uncertainties handling

The investment planning process in companies necessarily faces numerous uncertainties, mostly related to the evolution of the energy market and the advent of extreme events like energy crises. This is especially true when looking at many years in the future. All this considered, the results of a single run of a deterministic model provides questionable insights on the optimal configuration of a system. Therefore, the development of a robust energy strategy requires to carefully consider the uncertainties inherent to the input data [13].

Uncertainties can be taken in account by deterministic tools, analysing different scenarios and conducting sensitivity studies. However, the data structure of the tools should allow the modeller to handle and run a multitude of optimisations, ideally with little effort. Alternatively, tools employing a probabilistic approach can deal more systematically with uncertainties. As described in Ref. [108], the most diffuse probabilistic techniques in ESM are Monte Carlo Analysis, Stochastic Programming, Robust Optimisation and Modelling to Generate Alternatives.

Probabilistic models seem to present an advantage over deterministic ones in handling uncertainties. However, it should be stressed that the output of probabilistic models would be more complex to interpret and to report to the decision-makers. This holds especially true if we consider that companies currently lack the expertise to handle ESM. Therefore, the modeller should carefully ponder the inclusion of non-deterministic aspects in the energy system.

4.8. Targets

Beside the direct economic aspect, companies may pursue other objectives while planning their energy system. The Greenhouse Gas (GHG) saving is an important parameter, used to evaluate the environmental performance of a company. Investment planning models should be able to take in account GHG emissions, either by constraining their level or by setting an emission penalty. The latter may be of relevance for companies subjected to the Emission Trading Scheme (ETS) [109], or interested in evaluating the effect of the shadow price of emissions on the costs of the system [110]. Other companies may be interested in setting a target for local air quality. In that case, they should opt for models able to represent non-GHG emissions.

With respect to non-environmental constraints, companies may aim to achieve a certain level of independency from the grid, setting a minimum self-generation target, or even a renewable generation target. Moreover, the development of companies is bound to the site and the surrounding territory, in which their facilities are located. Therefore, a solid investment plan should take in account the availability of land and rooftops for the installation of renewables, as well as constraints on the availability of resources, e.g. biomasses, in the region.

While most energy system optimisation tools perform a solely economic optimisation, the possibility to set different objective functions [111] and multiple objectives criteria [112] represents an attractive opportunity to study the optimal configuration of the system under different and/or conflictual objectives. For instance, modellers may be interested in the study of company optimum versus social optimum [113], which can lead to significantly different configurations of the energy system.

4.9. Usability

Finally, the usability of a modelling framework is not of secondary importance in the selection of a suitable tool for a company. Generally, the accessibility and ease of use are a major determinant for the diffusion of open-source tools [114]. This is a major factor to consider, given that the application of ESM in companies is a rather new field of study.

It has to be noticed that the usability of a tool is a qualitative and somehow subjective issue. However, it is possible to identify some features which may contribute to this dimension. For instance, open-source models present an advantage in this sense, as the access to the code grants a higher transparency on the functioning of the tool and ample room for customisation. Moreover, those tools that are available free of charge, from the solver to the interface, present a lower price barrier with respect to their commercial counterpart.

An entry-level requirement for a high usability is the existence of a clear and detailed documentation [115], describing the input-data, the parameters, and the variables of the model, and complemented with examples and tutorials. Supplementary media, like online courses and workshops, can support users during the training period. Additionally, active forums can be an important resource to directly interact with the modelling community.

Finally, tools providing a Graphical User Interfaces (GUI), featuring reporting and visualisation capabilities, and granting access to databases hosting weather and typical building load data, can streamline the modelling workflow.

5. Results

This section presents the evaluation of the open-source modelling tools preliminary selected for the review. The screening methodology described in Section 3 yielded 17 tools, listed in Table 2. The modelling tools are evaluated side-by-side with one closed-source tool, DER-CAM, representative of the state-of-the-art of DES planning.

First, the tools are presented providing basic information such as the developing institution and programming environment. Secondly, the modelling tools are classified according to the scheme proposed by Ringkjøb et al. [28], and results are collected in three comprehensive tables. The ensuing sub-section discusses the suitability of the tools to support long-term investment plans for the energy system at the company-level, based upon the quantitative evaluation scheme

Table 2
Basic information on the modelling tools included in the analysis.[a] The Julia version is still under development, and it only features a subset of the functionalities of the Python version.

Name	Institution	First Release	Last Update	Programming Language	Scientific Reference/s
AnyMOD	TU Berlin	2020	2022	Julia (JuMP)	[116,117]
Backbone	VTT Technical Research Centre of Finland; University College Dublin	2019	2022	GAMS	[74,118–120]
Balmorel	RAM-lose	2001	2019	GAMS	[121–123]
Calliope	ETH Zürich	2015	2022	Python (Pyomo)	[124]
Ficus	Institute for Energy Economy and Application Technology	2015	2015	Python (Pyomo)	[84]
FINE	Institute of Energy and Climate Research	2018	2022	Python (Pyomo)	[125]
GENeSYS-MOD	TU Berlin	2017	2021	GAMS	[126,127]
NEMO	Stockholm Environment Institute	2020	2022	Julia (JuMP)	–
OSeMOSYS	KTH Royal Institute of Technology	2011	2017	GNU MathProg/Python (Pyomo)/GAMS	[128–130]
oemof (SOLPH)	Reiner Lemoine Institut, ZNES Flensburg	2015	2021	Python (Pyomo)	[131,132]
PyPSA	TU Berlin	2018	2022	Python (Pyomo)	[133]
REopt API	National Renewable Energy Laboratory	2020	2022	Python/Julia (JuMP)[a]	[83]
SpineOpt	VTT, KU Leuven, KTH, Energy Reform	2021	2022	Julia (JuMP)	[53]
Switch	University of Hawaii	2012	2021	Python (Pyomo)	[134,135]
TIMES	IEA-ETSAP	2000	2022	GAMS	[136]
Temoa	NC State University	2013	2018	Python (Pyomo)	[137]
Urbs	TUM EI ENS	2014	2019	Python (Pyomo)	[138]
DER-CAM	Lawrence Berkeley National Laboratory	2004	2022	GAMS	[139]

presented in Section 3. The full dataset used for the analysis, complemented with further information on the models, is provided in a spreadsheet format in the Supplementary Material.

5.1. Basic information on the modelling tools

The modelling tools included in the analysis are presented in Table 2. *Balmorel* and *TIMES*, developed in the early 2000s, are the most long-standing tools in the set[5]. A second group of tools is the product of the open-source movement which gained momentum from 2010 onward. This group includes *OSeMOSYS*, *Temoa* and *Calliope* among the others. The set also features six new-generation tools, which have been released during the last four years. Most of the tools have been updated after 2021, nine of them just last year, confirming that, generally, open-source models are actively developed and kept up to date.

The environment in which the models are coded can surely influence the modeller's choice. Different programming languages are used for the implementation of the tools. These range from algebraic languages, such as GAMS and MathProg, to general purpose languages like Python and Julia. For general purpose languages, the optimisation problem is formulated in domain-specific modelling environments, like Pyomo and JuMP. Most of these languages are open source, while GAMS requires a commercial license. More than half of the tools are written in the open-source Python language, confirming its popularity in the development of energy modelling tools [60]. However, four out of six of the tools released after 2019 are written in Julia, indicating that this modern language and its optimisation environment JuMP [140] are growing rapidly.

5.2. Classification of the modelling tools

Table 3 describes the general logic of the examined tools. The choice of restricting the focus of the review to optimisation tools which support investment decisions yielded a set of models which share a common logic. However, as ESM rarely fit into one category [56], it can be interesting to compare the full scope of the tools.

As regards the purpose, several tools are designed to support also operational decisions. These tools provide a running mode which suppresses the investment decisions and only optimises the dispatch of energy [12]. This functionality allows to test a configuration of the system obtained with the investment mode over a reduced horizon using, for instance, a smaller time-step and stricter operational constraints. Therefore, the technical feasibility of the solution can be assessed more precisely without resolving to a second, dedicated software. The set also features one tool, *PyPSA*, for the analysis of power systems, which is indicated in case the study poses particular emphasis on the design of electricity networks.

The programming technique is strictly related to the scale of the modelling framework and affects the operational constraints that can be implemented in the optimisation [38]. In Linear Programming (LP) models, relationships are formulated as fully linear expressions. This entails a low complexity of the system and short computational times [101]. Mixed-Integer Linear Programming (MILP) also formulates the problem using linear relationships, but introducing integer and binary variables. This allows to describe more advanced technical details, such as part-load efficiencies and on/off states of technologies [141]. Tools designed for small-scale systems, like *DER-CAM*, usually employ a MILP formulation. The majority of the tools under study, in particular the ones conceived for larger scales, are formulated using LP, but most of them also provide an option to switch to a MILP problem if needed. The tools already formulated with a MILP logic present and advantage with respect to the LP ones, as their functionalities can be extended to include advanced operational constraints without modifying the underlying programming technique.

Concerning the handling of uncertainties, only five modelling tools support a probabilistic approach. The remaining tools are deterministic, so uncertainties must be addressed with less systematic techniques, such as sensitivity studies.

Moving to the spatiotemporal features, Fig. 8 illustrates the typical scales of the energy systems the tools can be associated with. A different representation was used for the spatial scales for which the modelling framework was initially conceived (dark) and the scales for which the tool has been used in literature beyond its initial scope (light). The figure reveals the scarcity of available open-source tools to address the design of DES. Of the 17 tools considered, only two of them are purposely developed for system scales ranging from a single building to an urban district. Specifically, the objective of *ficus* is the optimal sizing of the energy system of a factory, while *REopt API* is used for the design of buildings, campuses, communities, and micro-grids. It is worth noticing

[5] Although *TIMES* was provided with an open-source license only in 2020.

Table 3
General logic of the modelling tools included in the analysis.[a] LP: Linear Programming; MILP, Mixed-Integer Linear Programming.[b] D: Deterministic; P: Probabilistic.

Name	Approach	Methodology	Purpose	Programming Technique[a]	Uncertainties[b]
AnyMOD	Bottom-up	Optimisation	IDS	LP	D
Backbone			IDS/ODS	LP/MILP	D/P
Balmorel			IDS/ODS	LP/MILP	D
Calliope			IDS/ODS	LP/MILP	D/P
ficus			IDS/ODS	LP/MILP	D
FINE			IDS/ODS	MILP	D
GENeSYS-MOD			IDS	LP/MILP	D
NEMO			IDS	LP/MILP	D
OSeMOSYS			IDS	LP/MILP	D
oemof (SOLPH)			IDS/ODS	LP/MILP	D
PyPSA			IDS/ODS/PSAT	LP	D
REopt API			IDS	MILP	D
SpineOpt			IDS/ODS	LP/MILP	D/P
Switch			IDS/ODS	LP/MILP	D
TIMES			IDS	LP/MILP	D/P
Temoa			IDS	LP	D/P
urbs			IDS	LP	D
DER-CAM	Bottom-up	Optimisation	IDS	MILP	D

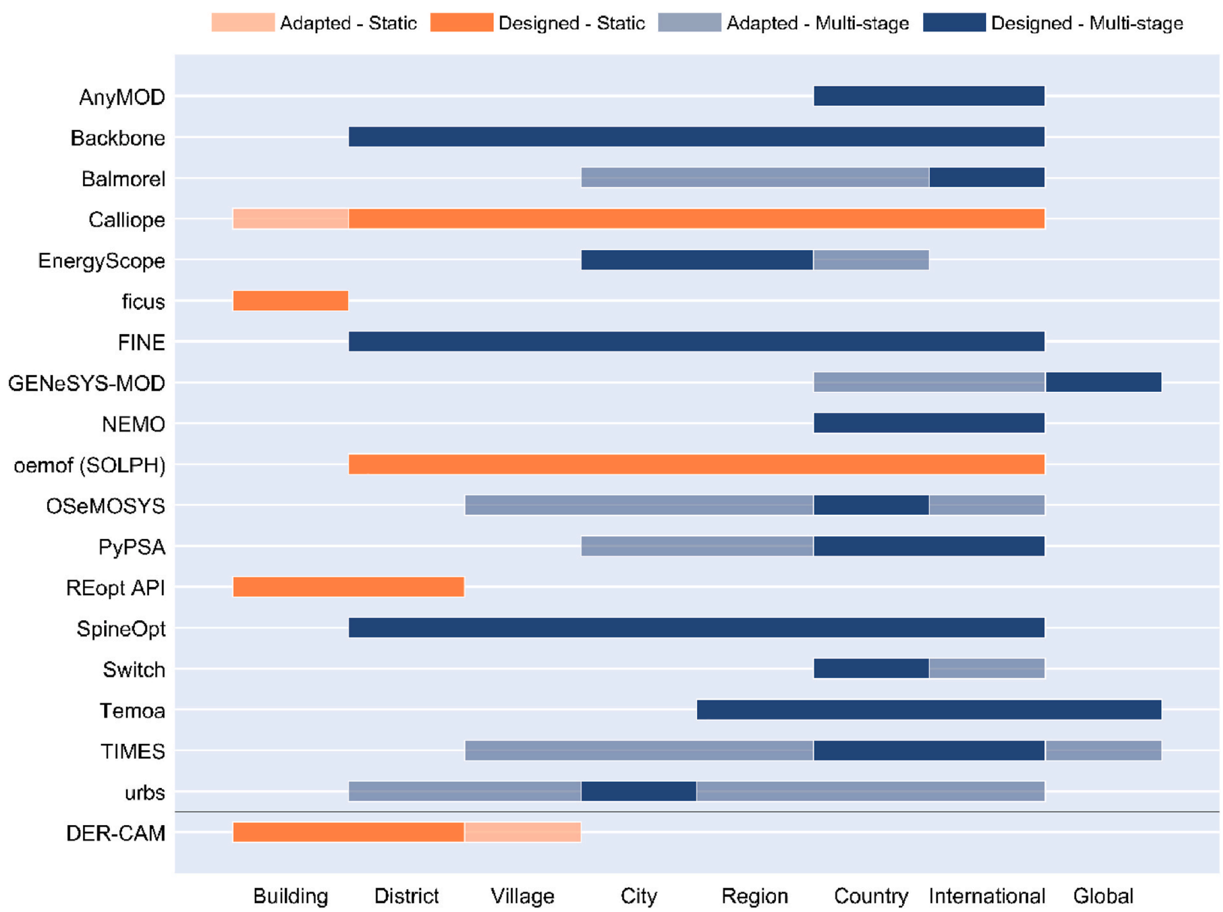

Fig. 8. Typical scales of application of the investigated tools. The dark bar pictures the scale for which the tool was initially conceived; the light bar shows the scales for which the tool has been used beyond its initial conceiving. The orange colour is used for static tools, while the blue colour refers to a multi-stage investment optimisation framework. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

that the application of a tool is rarely limited within the range of scales it was initially conceived for. For instance, *OSeMOSYS* was designed to support energy planning and policy assessment for large-scale systems [129]. However, since its first release it has been used to assess the development pathways of cities [142] and villages [143,144]. Other tools are developed with a scale-flexibility which allows to model energy systems of various sizes. This is the case for *Calliope*, *Backbone*, *FINE*, *oemof* and *SpineOpt*, which are suited for applications ranging from an urban district or cities [145–147], to entire countries and continents [148–150].

Fig. 8 also provides information on how the modelling tools handle the evolution of the system. An orange bar denotes a static approach, while a blue bar identifies a tool performing investment decisions on multiple stages. It can be noticed that the tools explicitly designed for DES belong, with no exception, to the static domain, while most of the tools designed for larger scales can instead offer insights on the development pathway of the energy system.

Table 4 reports further information on how the modelling tools deal with space and time. As concerns the time-scale, it can be observed that all the options described by Helistö et al. [68] are represented in the set. Tools designed for DES, like *REopt API* and *ficus*, preferably employ full time series, optimising decision variables across a single representative year. Other tools, such as *DER-CAM*, optimises the system reducing yearly time series to a set of days representative of different seasons and weekdays. The use of representative days and periods is also characteristic of the tools which have been previously labelled as multi-scale. These tools often provide functionalities for the selection of representative periods through TSA algorithms. For instance, *FINE* relies on the Python package *tsam* [151], *SpineOpt* has a dedicated TSA package, named *SpinePeriods* [152], and also *Calliope* supports TSA by mean of k-medoids algorithms.

As regards modelling tools conceived for large spatial-scale applications, such as national and international energy systems, time slices are the most frequent approach. In the time-slice approach, periods of the year which show similar characteristics (solar irradiation, energy demand, etc.) are hierarchically selected (for instance: seasons in the year, days of the week in the season, time of day) to define a set of typical days [69]. The time-slice approach is usually associated with a low time resolution [70]. However, this is a conception which derives from the traditional use of the models, rather than from their actual capabilities. As observed by Chang et al. [11], these tools are frequently used below their capabilities, mainly to reduce the computational effort. Models like *TIMES* have been used to model large energy systems, with numerous nodes and a wide array of technologies [153]. In order to reduce the computational intensity of such large systems, the number of time slices is generally limited between 1 and 12 [63]. Each time slice typically represents the night or day of the four seasons. Nevertheless, Table 4 shows that even large-scale models leave the choice of the temporal resolution to the users. Therefore, large-scale models are able to achieve hourly time resolutions, as demonstrated in several applications [142, 154]. Their use for high-resolution models of smaller-scale systems is not hampered by this aspect.

A final remark can be made on the spatial resolution of the tools. It can be seen in Table 4 that most of the tools employ a multi-node approach. These tools are thus suitable for modelling systems in which network constraints are important for the problem under study. Conversely, *ficus* and *REopt API* represent the energy system as a single node.

Table 5 gives an overview of the technical features of the modelling tools. It can be noticed that most of the models adopt a generic representation of conversion and storage technologies, leaving to the user plenty of scope in the design of the energy system. In addition, some of them address the physics of specific technologies. For instance, *oemof* contains a module which allows modelling the specific behaviour of CHP extraction units. Other tools, like *DER-CAM* and *REopt API* restrict the choice of the modelled technologies to a limited set of predefined units, like conventional conversion processes and renewable generators. This approach limits the space of the solutions available to the modeller. However, the range of technologies made available by these tools, especially by *DER-CAM*, should be able to satisfy the modelling needs of most companies.

As concerns the demand sectors covered by the modelling tools, also in this case the choice is frequently left to the user. Exceptions are *Balmorel*, *PyPSA* and *Switch*. *Balmorel* has a focus on the electricity and heating sectors, although add-ons exist which allow to model transport, gas, and hydrogen. *PyPSA* and *Switch* have been developed for power system studies, and therefore they focus on the electricity sector. However, *PyPSA* supports some options for sector coupling, like PtH, PtG and electric mobility. These tools are indicated only if the interest of the modeller lies in a specific sub-sector of the energy system.

The same flexibility demonstrated by the tools with respect to the modelling of technologies and energy sectors is not fully replicated in the representation of emissions. While some models can consider user-defined types of emissions, several tools can only address carbon dioxide (or equivalent carbon dioxide) emissions. Other tools, despite defining a limited set of emissions, can consider non-CO_2 and non-GHG

Table 4
Spatiotemporal features of the tools. Typical values are reported in brackets. UD: User-Defined.[a] Here, the level of foresight is only specified for the optimisation of investment decisions over multiple stages. It does not refer to the foresight used for the optimisation of dispatch decisions (i.e., perfect foresight or rolling horizon).

Name	Time Representation	Operation time-step	Horizon	System Evolution	Foresight[a]	Spatial Resolution
AnyMOD	Full time series	UD (from 1 h to 1 year)	UD	Dynamic	Perfect	Multi-node
Backbone	Full time series/Representative periods	UD	UD	Static/Dynamic	Perfect/ Limited	Multi-node
Balmorel	Time slices	UD	UD	Static/Dynamic	Limited	Multi-node
Calliope	Full time series/Representative days	UD	UD (1 year)	Static	–	Multi-node
ficus	Full time series	UD	UD (1 year)	Static	–	Single-node
FINE	Representative days	UD (typically 1 h)	UD	Static/Dynamic	Limited	Multi-node
GENeSYS-MOD	Time slices	UD (intra-day)	UD	Dynamic	Perfect/ Limited	Multi-node
NEMO	Time slices	UD (intra-day)	UD	Dynamic	Perfect	Multi-node
OSeMOSYS	Time slices	UD (intra-day)	UD (15–50 years)	Dynamic	Perfect	Multi-node
oemof (SOLPH)	Full time series	UD	UD	Static	–	Multi-node
PyPSA	Full time series/Representative days	UD	UD	Static/Dynamic	Perfect	Multi-node
REopt API	Full time series	15mi/30mi/1 h	1 year	Static	–	Single-node
SpineOpt	Time slices/Full time series/Representative periods	UD	UD	Static/Dynamic	Perfect/ Limited	Multi-node
Switch	Load curve/Time slices/Full time series/Representative periods	UD (typically 1 h)	UD	Static/Dynamic	Perfect	Multi-node
TIMES	Time slices	UD (intra-day)	UD	Dynamic	Perfect/ Limited	Multi-node
Temoa	Time slices	UD (intra-day)	UD	Dynamic	Perfect/ Limited	Multi-node
urbs	Full time series	UD (typically 1 h)	UD	Static/Dynamic	Perfect	Multi-node
DER-CAM	Representative days	15mi/30mi/1 h	1 year	Static	–	Multi-node

Table 5
Technical features of the tools. UD, User-Defined.[a] Conventional Generators, CG; Backup Diesel Generator, BDG; HyP, Hydropower; RoR, Run-Of-River; WP, Wind Power; PV, Photovoltaic; FC, Fuel-Cell; EL, Electrolysis; PtG, Power-to-Gas; CHP, Combined Heat and Power; GB, Gas Boilers; EB; Electric Boilers; HP, Heat-Pumps; GHP, Geothermal Heat-Pumps; AC, Adsorption Chiller; BEV, Battery Electric Vehicle; DAC, Direct Air Capture.[b] B, Electric Battery; T, Thermal Storage; H, Hydrogen Storage; CAES, Compressed Air Energy Storage; V2G, Vehicle-to-Grid.[c] But constraints and optimisation applied only to CO2.

Name	Commodities	Technologies[a]	Storage[b]	Demand Sectors	Emissions
AnyMOD	UD	UD	UD	UD	CO2
Backbone	UD	UD	UD	UD	UD
Balmorel	Electricity; Heat; Fuels	CG; HyP; RoR; WP; PV; CHP; GB; EB; HP	B; T	Electricity; Heat; Add-ons available for gas, hydrogen, transport	CO2; SO2; NOx; CH4
Calliope	UD	UD	UD	UD	CO2
Ficus	UD	UD	UD	UD	UD
FINE	UD	UD	UD	UD	UD
GENeSYS-MOD	UD	UD	UD	UD; Transport	UD
NEMO	UD	UD	UD	UD	UD
OSeMOSYS	UD	UD	UD	UD	UD
oemof (SOLPH)	UD	UD; complex CHP units	UD; CAES	UD	UD
PyPSA	UD	UD	UD; V2G	Electricity; Heat; Gas	$CO_{2,eq}$
REopt API	Electricity; Fuels	CG; PV; WP; CHP; GHP; AC; BDG	B; T	Electricity; Heat; Cooling	CO2, NOx, PM25
SpineOpt	UD	UD	UD	UD	UD
Switch	UD	UD	UD	Electricity	CO2
TIMES	UD	UD	UD	UD	UD
Temoa	UD	UD	UD	UD	UD
urbs	UD	UD	UD	UD	CO2, UD[c]
DER-CAM	Electricity; Natural Gas; Diesel; Biodiesel; Other	CG; CHP; RoR; WP; PV; FC; EL; AC; HP	B; T; H; V2G	Space-Heating; Water-Heating; Cooling; Natural Gas (for cooking); Electricity	CO2 (NOx for incentives)

emissions, such as NO_x and SO_2.

5.3. Suitability for application at company-level

In the previous section, the modelling tools were introduced and categorised according to a widespread classification scheme. That information provides an overview of the logic and capability of a tool, and could prove useful to screen the tools at the beginning of the selection process. This section dives deeper in the functionalities of the tools, comparing their performance over the nine modelling requirements needed to model company energy systems. To do so, the implementation in the models of over 100 functions was assessed. A score between 0 and 1 was assigned to the tools for each requirement, based on the capability of the tool to fulfil the functions in that requirement.

The graph in Fig. 9 ranks the modelling tools according to the overall score in the eight technical requirements and, separately, the score in the Usability dimension. The maximum score in the technical dimensions equals 8, but none of the modelling tools considered scored higher than 6. Three tools, *SpineOpt*, *Backbone* and *TIMES*, emerge from the set as the only ones able to significantly surpass the functionalities of

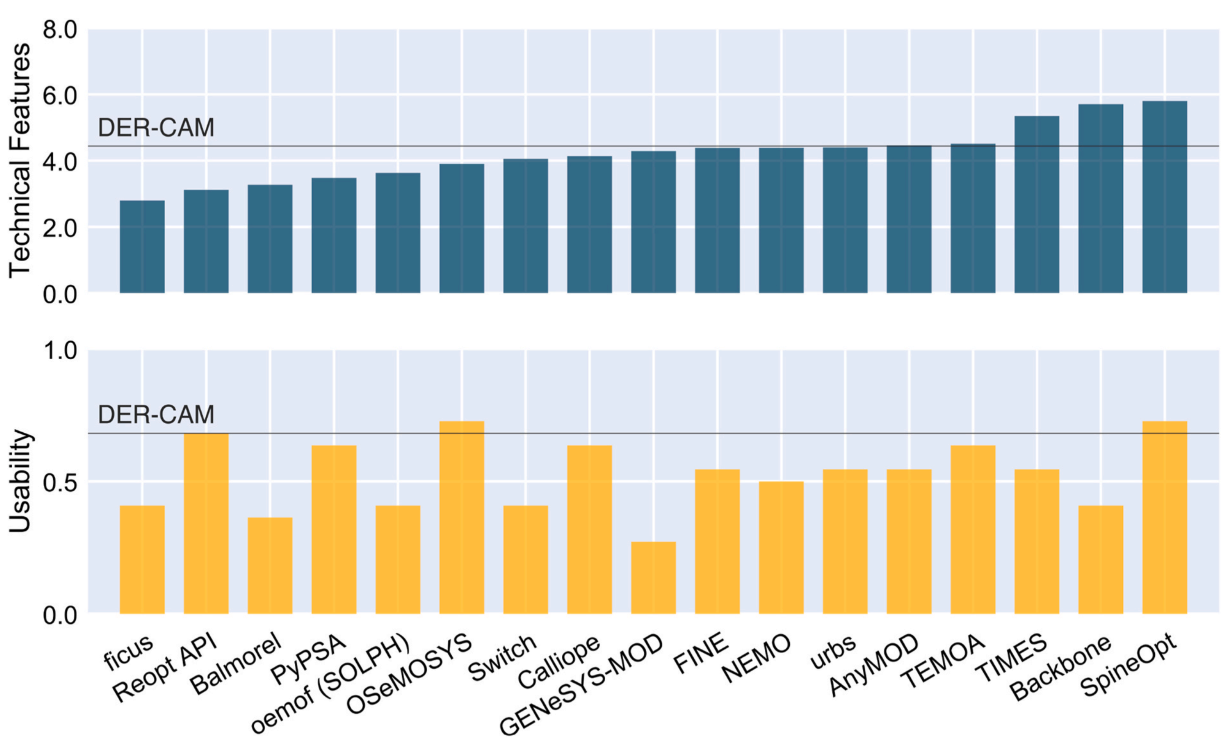

Fig. 9. Ranking of the modelling tools according to their capability to fulfil the eight technical dimensions and the Usability dimension.

DER-CAM. Among these tools, *SpineOpt* distinguishes itself for its high usability. Several other models, from *FINE* to *TEMOA*, closely match the score of *DER-CAM*. Surprisingly, the two open-source tools developed for the planning of DES, *REopt API* and *ficus*, are found at the low-end of the ranking. This is due, but not limited, to their static approach to the optimisation problem and their inability to model energy networks.

A break-down of the evaluation of the performance of the tools in all the modelling requirements is shown in Fig. 10. Four performance categories are defined, *low*, *medium*, *high,* and *very high*, each characterised by a colour in the figure.

The importance of representing detailed operational constraints in investment planning models have been frequently remarked in this paper. It can be observed that *DER-CAM* offers a high technological resolution, including operational details ranging from ramp-up/down constraints to minimum operational levels and part-loads. As concerns large-scale models, such as *AnyMOD*, *OSeMOSYS* and *Temoa*, the representation of technologies is often simplified. At the low-end, technologies are represented as fully flexible units with constant efficiency (*OSeMOSYS*). A more advanced representation see the introduction of ramping constraints (*GENeSYS-MOD*, *NEMO*) and time-step dependent efficiencies (*Calliope*, *Temoa*). More advanced tools, such as *Switch*, and multi-scale models like *FINE* and *Backbone* can model part-load efficiencies and impose cyclic constraints on the operation of a technology and/or start-up/shut-down constraints. In this way, they enable the optimal scheduling of conversion technologies.

TIMES, Backbone and *SpineOpt* reach the highest performance in the System Operation requirement. *TIMES*, even though mainly conceived for large-scale systems, offers a wide set of parameters to constrain the operation of a technology. Moreover, it can be expanded beyond its core capabilities to represent LP and MILP versions of the scheduling problem, and part-load efficiencies. *SpineOpt*, in addition to a rich set of constraints, has a unique temporal structure [53], which allows the modeller to selectively introduce complexity where needed. In this way, different parts of the system can have different time-resolution. For instance, the dynamics of the electricity sector can be modelled with higher resolution and detail, without increasing the complexity of the more stationary heating sector. This flexibility was not found in any other model, even though *AnyMOD* provides an option to model different sectors with different resolutions. In addition, *SpineOpt* adopts advanced mathematical techniques to reduce the computational intensity of the model. The long-term investment problem and the short-term operational problem can be decoupled through the Bender's decomposition technique [155]. In this way, the concurrent optimisation of long-term decisions and short-term operation is possible. Moreover, the operational sub-problem could be optimised using a rolling window, thus further reducing the computational burden.

As regards the representation of flexibility options, all the modelling tools provide a minimum level of detail. The most basic modelling of storage includes charge and discharge efficiency, constraints on the depth of discharge and on the charge/discharge rate (i.e., *OSeMOSYS*, *REopt API*). More advanced representations of storage consider storage losses, investment in both capacity and power capacity, and constraints on the cycling of storage, as in *ficus*. *DER-CAM*, *urbs*, *FINE*, *oemof* and *Switch* have also implemented DSM options.

As concerns the Transactive Market requirement, both *DER-CAM* and *REopt API* can model complex tariff structures, including charges for

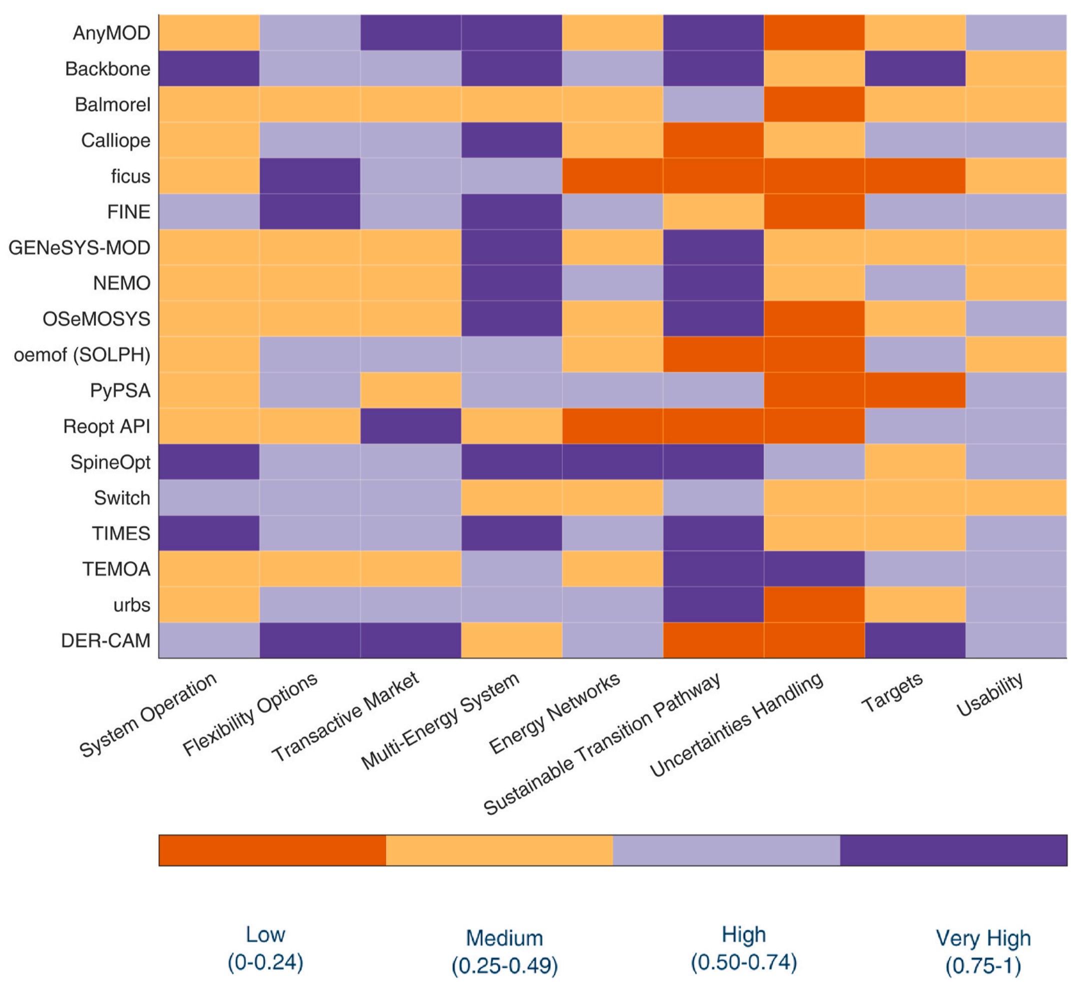

Fig. 10. Breakdown of the capability of the modelling tools in the nine modelling requirements.

peak demand periods and tiered prices for electricity. *ficus* achieve a high score too, because of its consideration of peak-demand tariffs. Conversely, large-scale models can usually represent only simple tariffs, assigning a marginal price to the unit of electricity sold/purchased, or fixed charges independent on the consumption (OSeMOSYS*, GENeSYS-MOD*). More advanced representations (*Calliope*, *FINE*, *urbs*) allow to model the variation of electricity price according to the time of the day or the year. One noticeable exception is *AnyMOD* which, although designed for macro-systems, explicitly models complex import/export prices, including tiered prices.

In the Multi-Energy System requirement, sector specific tools such as *Switch*, *Balmorel*, and *PyPSA* perform worse than the others. Similarly, the modelling tools relying on a limited subset of predefined technologies and storage, like *DER-CAM* and *REopt API*, cannot provide the necessary flexibility to model a wide variety of alternatives and sector-coupling options. However, it should be considered that *DER-CAM* allows to model some interactions between different sectors, like PtH, PtG, and vehicle-to-grid. Tools like *oemof*, *Temoa* and *urbs*, which adopt a flexible definition of technologies and energy demands, belong to the *high* performance band. An even higher level is reached by those tools supporting fuel-switching functions and alternative modes of operations (i.e., *OSeMOSYS*, *Calliope*, *AnyMOD*).

Energy networks are represented with a significantly different degree of detail by the tools under investigation. *DER-CAM* can describe the physics of electric power flows (DCOPF) and thermal networks. Conversely, *REopt API* and *ficus* totally neglect transmission bottlenecks. Most of the tools in the *medium* band represent networks through simple transport models, defining a transmission efficiency and capacity. More advanced models, like *FINE*, *PyPSA* and *urbs* can model the physics of the electricity system as a DCOPF problem. *PyPSA*, which is designed for power systems analysis, also support the optimisation of the power flow under security constraints (SCOPF). Finally, *SpineOpt* achieves the highest score in this category, thanks to its ability to model not only the DCOPF and SCOPF of the electricity system, but also specific physics of thermal networks.

Unsurprisingly, the Sustainable Transition Pathways is another modelling requirement in which the capabilities of DES and large-scale tools diverge significantly. *DER-CAM*, *REopt API* and *ficus*, because of their static approach, are unable to represent long-term dynamics. *REopt API* partially addresses this problem defining an escalation rate for the price and the carbon content of the electricity sourced from the grid. On the opposite side of the rank, multi-stage investment optimisation tools like *OSeMOSYS*, *Temoa*, and *AnyMOD* enable the detailed modelling of the evolution of the energy system and its surroundings. These tools can account for the long-term variation of a number of factors: the energy demand, the prices of fuels and electricity and their carbon intensity, the price of carbon, the technical advancements etc. They also allow to set year-dependent targets, like minimum share of renewable generation and emission limits. Other multi-stage tools implement only a subset of these functionalities. For instance, *Balmorel* allows to vary the price of fuels and electricity across the modelled horizon, but the investment costs and the emission factors are kept constant.

It is worth noticing that, as illustrated in Fig. 10, the most performing tools in the Transition Pathway category are generally the ones with the lowest score in the System Operation category. Thus, a trade-off between these two modelling aspects is inevitable for most of the tools. On the contrary, *SpineOpt*, *Backbone* and *TIMES* reach a high score in both categories.

As already observed from the classification of the tools, only five of them systematically address uncertainties. Among them, *Temoa* offers the widest range of options to perform uncertainty analysis. These include Monte Carlo Simulations [156], modelling to generate alternatives [157] and even stochastic programming. *Calliope* implements a particular formulation of modelling to generate alternatives, named SPORES, which allows to find near-optimal configurations of the system with an emphasis on maximising the diversity of solutions [158]. *TIMES* and *Backbone* support stochastic programming, while *SpineOpt* implements both stochastic programming and modelling to generate alternatives. In addition, *SpineOpt* presents a flexible stochastic structure which, similarly to the temporal structure, allows to model uncertainties only for selected components of the system. This characteristic, which was not fully captured by this scoring system, enable the treatment of uncertainties in complex models, keeping the increase in the computational effort to a minimum.

The last technical dimension is the Target category. Relatively to this dimension, *DER-CAM* can take in account disparate targets and constraints relevant for the design of DES. In the first place, it can minimise both system costs and emissions, a functionality which is emulated only by four open-source tools (*Calliope*, *oemof*, *Backbone* and *urbs*). In contrast, *ficus* does not take into consideration any environmental impact. Also, *DER-CAM* explicitly models the availability of resources and land for the installation of renewables. While the availability of resources is considered by all tools, only some of them address the problem of land use. However, it should be considered that several modelling tools allow to set capacity constraints for groups of technologies, providing a workaround to address this issue. The same consideration can be applied for targets such as self-generation and renewable shares which, even though not explicitly modelled, could be easily implemented in most tools.

Lastly, some considerations can be made on the Usability of the tools. *DER-CAM* achieves a high score in this dimension, thanks to a user-friendly interface, granting access to databases hosting weather and building loads data[6]. Also, online courses are available. Similar utilities are also supported by *REopt API*. *SpineOpt*, besides holding the first position in terms of technical features, is also characterised by a high usability. The coupling of the model with the user interface *Spine Toolbox* [159] eases the management of data flows and the handling of the modelling steps. Additionally, despite its recent release, a clear and detailed documentation and training materials are provided. *TIMES* demonstrates a high usability too, mainly because of the support of a GUI (*VEDA*), reporting capabilities, data management, and the active ETSAP community. However, the GUI is very expensive[7] which is likely to limits its application. In contrast, the high accessibility of tools like *OSeMOSYS*, *Calliope*, *Temoa*, and *urbs* is worth to be stressed. All these tools are well documented, with an extensive description of the parameters, variables and equations implemented in the code. Moreover, they can be run free-of-charge from the programming language to the solver. This is in contrast with other tools which are penalised in the usability dimension because, even though open source, they require additional commercial software. This is, for instance, the case for *Balmorel,* Backbone and *GENeSYS-MOD*, which are written in GAMS.

6. Discussion

In the previous section, we evaluated the suitability of available open-source models to support the development of a long-term energy strategy at the company-level. Only tools employing an investment optimisation methodology were considered, and large-scale models supporting multi-stage investment optimisation were also included in the analysis.

Of the 17 tools examined, only two (*REopt API*, *ficus*) are explicitly designed for spatial scales comparable to that of a company. Moreover, a group of tools (*FINE*, *SpineOpt*, *Backbone*, *Calliope*) can be denoted as multi-scale, as they can model energy systems ranging from an urban district up to entire continents. Comparatively, a much higher number of tools have been developed to support energy-planning at larger scales, especially the country-scale. This trend reflects the need for mathematical models to support decision-making at the national level in order

[6] Although the availability of data is restricted to the US.

[7] http://www.iea-etsap.org/tools/ETSAP-Tools-License-Pricing.pdf.

to meet the ambitious goals set by the Paris Agreement [160]. However, it also reveals that the development of open-source tools to explore the effects of national policies on local actors, such as private companies, is still missing.

The few open-source tools designed for small-scale systems invariably belongs to the static class. Therefore, the development of a long-term investment plan in companies requires the adaptation of large-scale modelling tools, or the adoption of a multi-scale tool. Either way, a trade-off between the ability to characterise the evolution of the system and the other modelling dimensions is required. In particular, the Transactive Market and System Operation dimensions present the major challenges.

While tools like *DER-CAM* and *REopt API* achieve a high score in the Transactive Market dimension, large-scale tools allow only a simplified representation of utility tariffs. Therefore, in case the interest of the study lies in the exploration of the energy system of a company under complex utility tariffs, the modeller should resolve to tools like *REopt API* and *DER-CAM*. Alternatively, the capabilities of large- and multi-scale models should be expanded accordingly.

Models reaching a high score in the Sustainable Transition Pathway dimension (*OSeMOSYS*, *TEMOA*, *AnyMOD*, etc.) usually perform poorly in the System Operation dimension. These tools could provide valuable insights on the optimal evolution of the system. However, the over-simplistic representation of the operational aspects requires to test the technical feasibility of the optimised configurations. This might require a second tool, more focused on the operational aspects, like a dedicated simulation tool.

By contrast, some tools in the multi-scale group (*SpineOpt*, *Backbone*, *TIMES*) provide the best compromise between the modelling of short- and long-term dynamics. These tools are therefore indicated to conduct detailed and robust investment planning studies in companies. Among them, *SpineOpt* distinguishes itself for its unique temporal and stochastic structure. This tool could enable the study of technically detailed systems in the long-term, while keeping the model computationally tractable. Moreover, the user-friendliness of *SpineOpt*, and the fact that it is completely free-of-charge, may contribute to its diffusion. On the contrary, *TIMES* presents a substantial financial barrier which is likely to hinder its application in companies. Fig. 11 shows that, as of today, *SpineOpt* outperforms *DER-CAM* in most of the modelling dimensions considered in this review.

This review work provides a thorough assessment of more than 100 specific modelling functions across 17 open-source models. The information reported in the Supplementary Material can support modellers in the selection of tool suitable for their specific applications. However, despite the highly detailed comparison of the tools, several important modelling functions could not be included. For instance, the representation of relevant energy markets other than the electricity one was not assessed. Other pieces of information were not collected because of the difficulty in retrieving reliable and comparable data from literature. These include the frequency of update of databases and models' runtimes.

Moreover, it could be argued that a more insightful comparison of models could be attained through the testing of different models with a harmonised energy system and scenario. However, this investigation methodology is highly time-consuming, and requires an operative knowledge of the different modelling tools. Performing this analysis over 17 different tools would probably be impracticable. However, the information provided in this review could enable the selection of a subset of promising tools to be further investigated in future works.

A final remark is made about the final users of these tools. The selection of the modelling requirements and functions made in this review was based on the ideal capabilities that a tool should possess to support long-term energy planning at company-level. Nevertheless, it has already been remarked that most companies currently lack the expertise to handle such type of modelling. In this sense, the availability of advanced, but complex, modelling functions could be a drawback rather than an advantage. For instance, probabilistic models allow to systematically handle uncertainties, but they are way more complex to use and to be interpreted. Similarly, having a pre-defined set of technologies could streamline the use of the tool, although at the expenses of its flexibility. This considered, the adoption of energy system models by companies should be initially mediated by an external group of modellers, meanwhile the necessary expertise is internally developed.

7. Conclusion

Private companies are expected to step forward on the road to energy transition, clearing the way for the deployment of renewable and sustainable energy through substantial investments in green and clean technologies. However, the transition towards a sustainable energy system requires industrial stakeholders to make careful considerations about long-term dynamics, such as the escalation of the prices of fuels and electricity and the commercial availability of innovative technologies. Therefore, companies may benefit from the support of mathematical models for the roll-out of long-term energy strategies.

In this paper, we have reviewed energy system modelling tools to

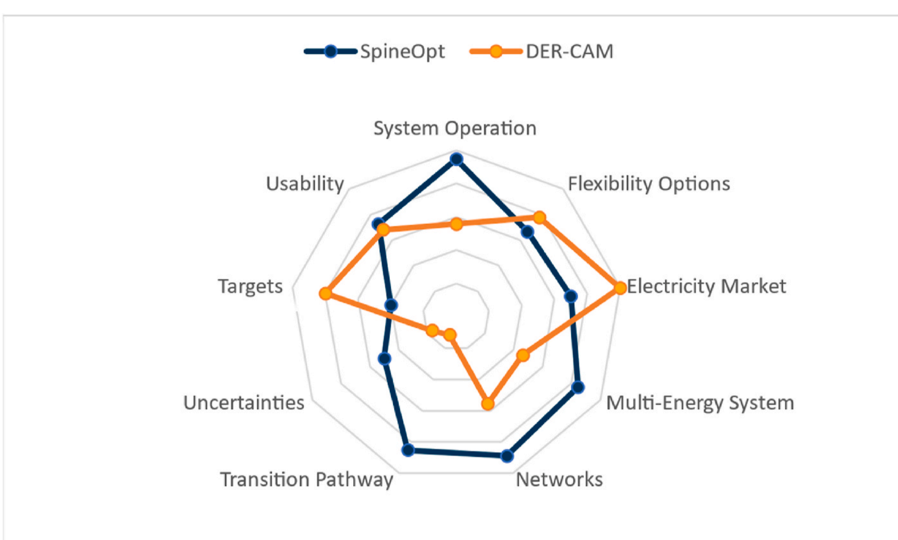

Fig. 11. Final comparison of the most features-rich open-source tool (SpineOpt), with the reference closed-source tool (DER-CAM).

assess their suitability for application at the company scale. Having recognised a gap to be filled in the existing body of knowledge, contrarily to most other reviews on distributed energy systems models, we focused on open-source optimisation tools, able to serve as investment decision support tools. Moreover, acknowledging that tools designed for distributed energy systems are generally unable to consider long-term dynamics, we decided to include large-scale tools in the analysis. The capability of the tools to support reliable investment studies at the company-level was quantitatively determined evaluating their performance in nine modelling requirements identified in literature.

The outcome of the review indicates that few open-source tools are appositely designed to support energy planning at the local level. In addition, the few tools available are not suited for the design of a transition pathway. Large-scale models are generally able to include long-term dynamics, but this comes at the expense of the detailed representation of the operation of the system. Moreover, large-scale models were generally found unable to represent complex but key aspects of the energy system, such as different utility tariffs. Presently, a trade-off between long-term planning and peculiar aspects of the energy system of a company is inevitable.

Based on specifically designed indicators, the best compromise is offered by multi-scale tools like *Backbone, TIMES* and *SpineOpt*. These tools can cover many aspects of long-term planning, while maintaining a high technological resolution. Among them, *SpineOpt* demonstrated a unique temporal and stochastic structures, which could enable the long-term study of highly detailed systems. Moreover, the framework is user-friendly, fully open-source and free of charge. On the contrary, *TIMES* presents a major financial barrier, which is likely to hinder its adoption by companies.

Addressing the gap in the existing body of knowledge, the information here provided can help the selection process on various levels: from a preliminary screening of the tools, based on general features, to the assessment of the availability of specific modelling functions. It is stressed that the ranking of the tools proposed in this paper reflects their ability to fulfil specific requirements laid out in this paper, rather than their overall capabilities. Moreover, it is acknowledged that the choice of a tool heavily depends on the particular case under study. To enable modellers to make informed choices based on their specific research questions, four detailed tables describing the features of the tools and a list of over 100 functions are made available in the Supplementary Material.

Credit author statement

Lorenzo Laveneziana: Conceptualization, formal analysis and data-curation, Writing- Original draft and final preparation, Matteo Prussi (corresponding author): Conceptualization, Methodology, Writing-Original final preparation., David Chiaramonti: Review, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Matteo Prussi reports financial support was provided by European Commission.

Data availability

All the data used for the reserach are reported in the paper, and complemented by the supplementary material.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esr.2023.101136.

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