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Review of cost objective functions in multi-objective optimisation analysis of buildings

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A R T I C L E I N F O

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A B S T R A C T

Notwithstanding the reductions in the cost of renewable energy per unit produced, cost objectives remain a relevant yet understudied topic due to their ability to indicate information available in the market. To better understand the general practice and identify trends in cost objectives for renewable energy-powered buildings in multi-objective optimisation problems, the article systematically reviews 129 studies published in 2011–2023 and identifies the highly cited articles (N = 23) to be reviewed narratively. As for the contribution to the literature, cost objectives are re-categorised based on the cost components considered. Assigned categories show that the authors focus on initial costs and energy costs. Systematic analysis shows that the most popular original metrics are total (life cycle cost, total costs) and energy import costs. There seems to be little association between climate zone and metric considered, but the payback period is applied in less developed countries. Supplementary economic objective metrics are on the rise. To further aid decision-making and address the current limitations – oversimplification of the project context, transitioning towards a managerial accounting perspective is welcomed. It could aid in attracting investment from other than project developers' sources, to reach the target investment in building energy efficiency required for the 1.5-degree target by 2050.

1. Introduction

The electricity grid is increasingly powered by renewable energy reaching 28.7 % in 2021, and innovation in "clean" buildings is booming, with 45 % of the late-stage venture capital investment going towards the companies designing or developing the building envelopes withover 40 % being directed towards the buildings energy management system-focused start-ups. However, from a future perspective, energy efficiency investment, at 0.3 USD trillion annually in recent years, *versus* investment needs are not in line to achieve 2050 goals. Energy efficiency in buildings must be scaled massively – by 11.2 times in 2021–2030, compared to 2017–2019 [1].

Although venture capital is pulled towards energy-efficient building solutions, start-ups have a limited capacity for research and development investment. Therefore, solutions to RE-building demand optimisation for higher efficiency should be carried out elsewhere, including the public sector.

The economic objectives employed when studying buildings with RE have been overlooked and not examined in the necessary detail to provide a better understanding for modelling to both the research community and practitioners. It may be argued that RE costs are decreasing relative to energy produced, and therefore also in their importance to project managers. However, structure of the costs of the RE sources is fundamentally different from traditional ones, with less (or none) fuel and opportunity costs [2], and therefore calls a further examination. In addition to different cost structure, cost objective comprehensiveness applied in studies varies widely. It depends on whether the overall project cost reduction (i.e., for installation of solar panels as in Ref. [3]), the cost reduction of its components, i.e., energy costs [4], or investment costs [5], or the shortening of the period for investment recovery [6] is considered. Still, scientific literature on these aspects is largely obscure.

Economic objectives are not only relevant, but also highly important due to the mostly accepted view that when information arises, it is quickly incorporated into prices [7]. With competitive markets, in turn, prices equal marginal costs, so the costs are a good proxy for freely available information. Despite the importance and relevance of the economic objectives, no recent semi-systematic review has been carried out focusing on the cost functions in buildings with RE (for related, see Table 1), or they have been given a minor role [8,9]. Studies have rarely reviewed cost metrics, and when they have, it has been in conjunction

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Abbreviations

ACS	Annualized cost of system
ACSR	Annual cost saving rate
AEC	Annual energy costs
ATLCC	Total annual levelised cost flow
COE	Cost of energy
CS	Cost savings
CvaR	Conditional value at risk
DPB	Discounted payback
DPP	Discounted payback period
EAC	Equivalent annual cost
EC	Energy cost
ELCC	Equivalent life cycle cost
ELCE	Equivalent levelised cost of energy
GC	Global cost
GPC	Grid penalty cost
GPC	Grid penalty cost
IC	Investment cost
LCC	Life cycle cost
LCOE	Levelised cost of energy
MC	Maintenance cost
MOO	Multi-objective optimisation
NPC	Net present cost
NPV	Net present value
NTC	Net total cost
nZEB	net (nearly) zero energy building
O&M	Operation & maintenance cost
OC	Operational cost
PBP	Payback period
R&D	Research and development
RE	Renewable energy
ROA	Real options approach
RQ	Research question
SPB	Simple payback period
TA	Total annuity
TAC	Total annual cost
TC	Total cost
TCO	Total cost of operation
TIC	Total investment cost
TPC	Total power cost

with rather technical aspects, to lesser extent – energy aspects.

Knowing the lack of a comprehensive review of the economic objectives in buildings with RE, this study reviews the economic objectives, in particular, cost objectives, to assess the factors that are likely to be related to the cost metrics. In doing this, the study bridges the research gap by:

- assigning cost metrics based on the cost components;
- relating the assigned cost metrics to development level;
- analysing the dynamics of supplementary metrics and uncertainty in models.

The main findings respective to policy makers uncover the need to considered public incentives with greater granularity. For industry, the main area for improvement lies in consideration of managerial flexibility in investment projects which shold first be supported by more research. Moving towards life-cycle approach, more comprehensive abosulte metrics should be used including more cost components. The rest of the study is structured as follows: Chapter 2 describes the methodology, Chapter 3 gives theoretical background and reviews the highly cited works' cost objectives in detail, Chapter 4 systematically analyses cost objectives by their components, Chapter 5 discusses the results, and Chapter 6 provides the conclusion and future research.

2. Research design and methodology

In the literature review a semi-systematic approach is applied to give an overall view of the state of the art in cost modelling. The goal of the review is to assess the economic objective functions applied to multi-objective optimisation (MOO) problems in buildings with RE production.

2.1. Research questions

To this end a literature review was conducted, answering the research questions, namely:

RQ1. What cost metrics and components thereof are primarily used?

RQ2. How can cost-objective approaches be grouped?

RQ3. Does the development level and climate zone of the case study is associated with the cost metric choice?

RQ4. What are the dynamics and future trends of cost objectives?

2.2. Search process

The search process was conducted in January 2023 on the "Scopus" website containing the words "renewable" and "energy", and "cost", and "building", and "multi-objective" in title, abstract or keywords. The search was limited to articles in the English language and yielded 148 articles. The threat of missing and/or biased evidence [12] is outweighed (or, at least, motivated) by the quality of sources and ease of screening the articles found [13]. However, authors recognise the possible limitations regarding lack of comprehensiveness in search sources when exclusing grey literature and non-English language articles. Following this stance, 146 articles were retrieved in full text (two were not openly accessible). During article screening, the reasons for the exclusion of 17 articles were due to not being a case study (N = 2), not concerning a building (N = 6), not concerning renewable power generation (N = 2), cost function not being specified (N = 8), or other (N = 3). The design of the study can be seen in Fig. 1.

Table 1
Comparison of most relevant reviews published on cost objectives and the review.

Reference	Year	Technical aspects	Energy aspects	Social aspects	Economic aspects	Optimisation focus	Cost focus
[10]	2016	×	✓	×	✓	✓	×
[8]	2018	×	×	×	✓	✓	×
[11]	2020	✓	×	×	✓	×	✓
[9]	2021	✓	✓	✓	✓	×	×
This study	2023	×	✓	×	✓	×	✓

Note: Hereafter, ✓ denotes inclusion and × exclusion.

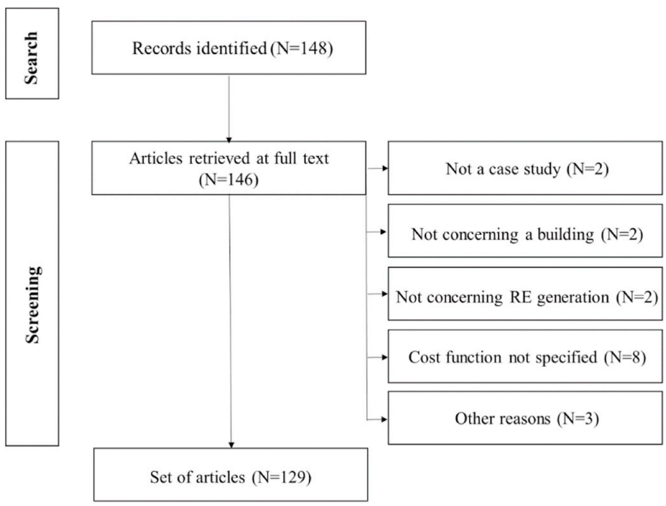


Fig. 1. Design of the study.

2.3. Data extraction and analysis

The information on life cycle cost components, citation metrics of the journal and year of the publication were collected from the article and Scopus website [16]. In an attempt to describe the most influential articles, their impact is calculated by either of the following rules. The first rule includes articles in the 90th percentile of citations in January 2023 per CiteScore of the journal for the respective year (N = 19). The second rule includes articles with more than 100 citations as of January 2023 (N = 6). These two rules together yield 23 unique articles to be reviewed and discussed in-depth (see Table 5). Though sparingly, other articles are discussed when authors find it informative.

To explore and confirm the findings from literature with other data, development level data [17] and Köppen - Geiger climate zones classification [18] were obtained. The collected data were described using software “Stata” [19] and “R” [20] to show the following items (Table 2).

3. Overview of cost objectives

The problem in buildings with RE concerns finding an optimal operation of electrical load in terms of favourability to end users and economic considerations [21]. The technical aspects of the problem can be embedded into assumptions regarding the power generation, or they

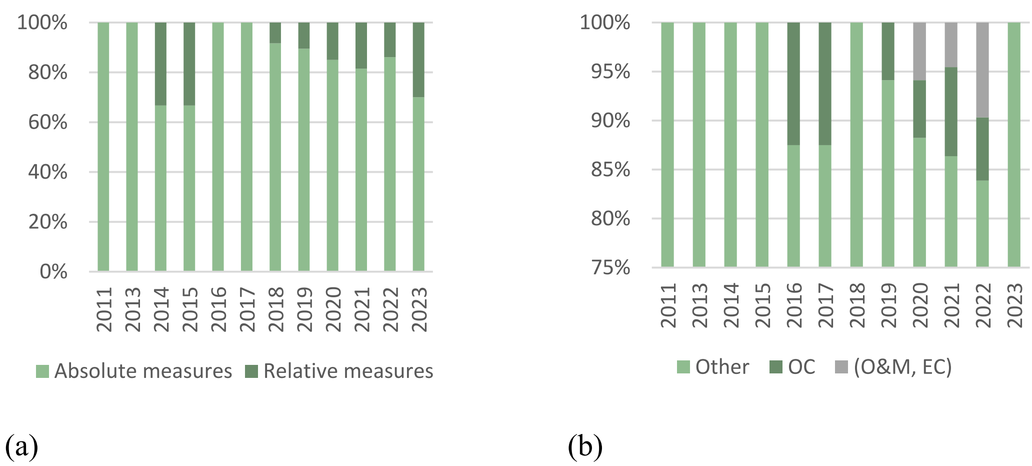


Fig. 2. Studies considering relative and absolute (a), and operating cost (OC, and {O&M, EC}) cost measures (b) over the years.

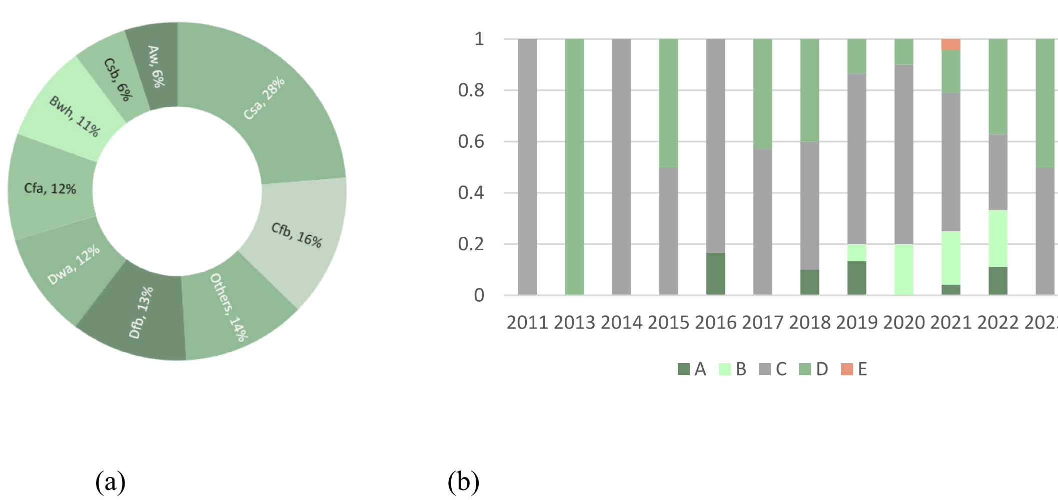


Fig. 3. Köppen - Geiger climate zone subgroups (a) and groups over the years of case studies (b).

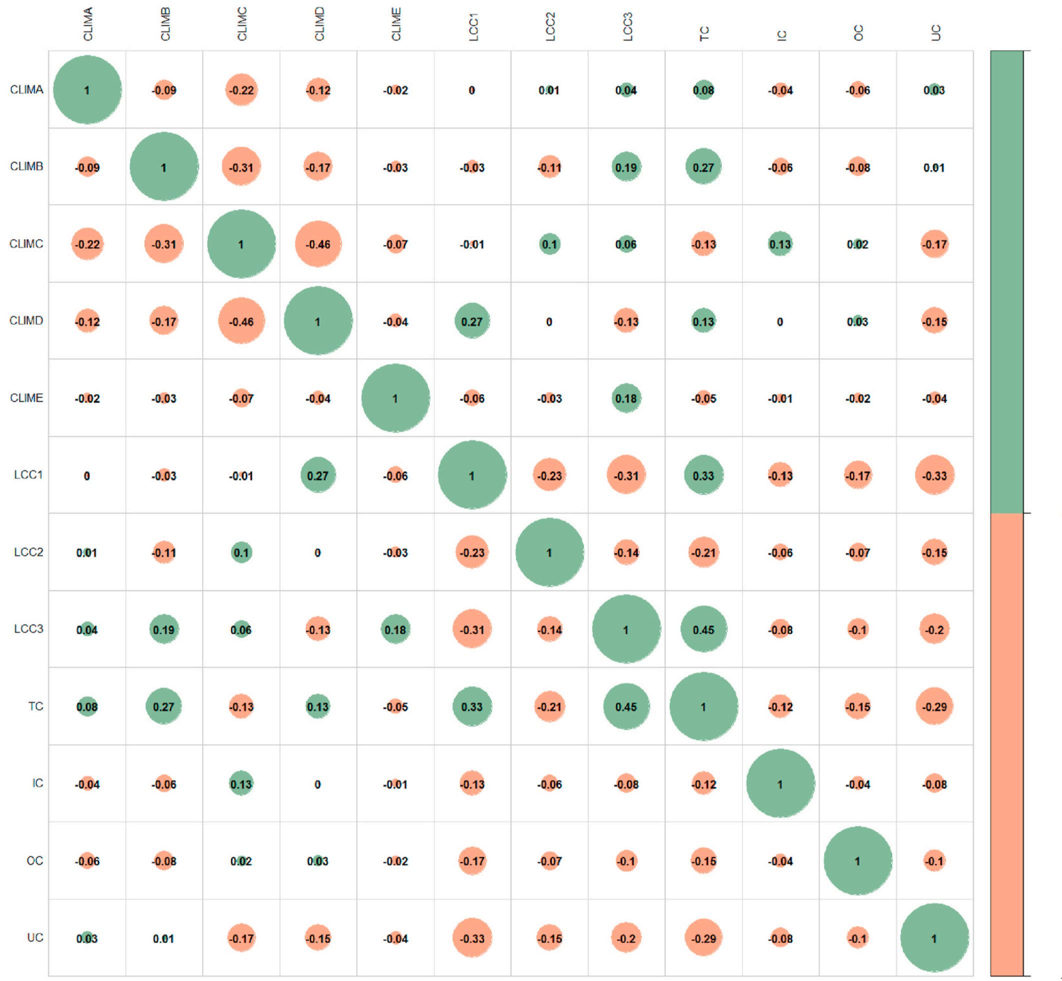


Fig. 4. Correlation between climate zones and assigned metrics.

can be abstracted from (e.g., generation being independent of cells, the configuration and efficiency [21]). The problem on the production side can be simplified by assuming exclusive operating time slots [22]. Lastly, regarding energy storage, the battery energy levels at the end of the operating period can be assumed to be equal to the start of the next period [23]. Technical aspects enter the optimisation problem via constraints as well. For example, shiftable loads have been constrained to an acceptable range of operation [24,25].

Attention may now be directed from technical to economic objectives. No attempt is made to cover social aspects, that is, resident well-being. Cost objectives (as named by the authors of the respective studies, and hereafter referred to as “original” metrics) are listed in Table 3. Cost metric approaches can be grouped according to the comprehensiveness of the costs considered over the project lifetime, and the calculation of absolute or relative costs incurred. The comprehensiveness of the cost metric approach is proxied by a number of LCC components considered: investment cost (initial investment and residual value), operation cost (maintenance and replacement), utility cost (energy consumed and sold), and other (i.e. uncertainty consideration and government incentives), as categorised by Ref. [15]. The absolute or relative value, in turn, is defined as the calculation of absolute cost/time to recoup the cost, or calculation of relative cost (i.e. with respect to energy produced, or baseline scenario).

3.1. Definition and theoretical considerations

The overview of definitions and sources is given in Table 3. Absolute NPV-based metrics (such as LCC, TC) or simpler alternatives, such as payback period or specific LCC components, such as IC, EC and O&M, or a mixture thereof, are defined. Moreover, relative metrics, such as LCOE, ACSR and exergy cost, are also listed.

As can be deducted from Table 3, a wide variety of constructs has been applied to economic objectives, most commonly – costs. Nevertheless, these objectives can be divided into absolute and relative measures, and specific cost components. From these, the absolute and specific components approaches are the most popular. The major limitations of absolute measures are the oversimplification of the project context. Payback-based absolute measures in their simplest form tend to ignore the time value of money, while with measures like LCC and TC, it is up to studies to define the scope of cost calculation.

3.2. Application of LCC

As previously stated, the specific and the absolute metric groups are the most common. More specifically, the focus of power usage in reviewed studies is contradicted by the consideration of the LCC, albeit the latter being defined differently (concerning comprehensiveness) from author to author. Earlier works, such as Stadler et al. [123], and Chu et al. [29] with the multi-objective optimisation method consider the annual energy costs, which include the energy purchase cost, the amortised distributed energy source technology capital cost, and the annual O&M costs.

Models with LCC have progressed in both ways – by simplifying, and by expanding in cost comprehensiveness. That is, previously largely

Fig. 5. Case studies considering hybrid generation (a), secondary economic objective metrics (b) and all studies considering government payments (c).

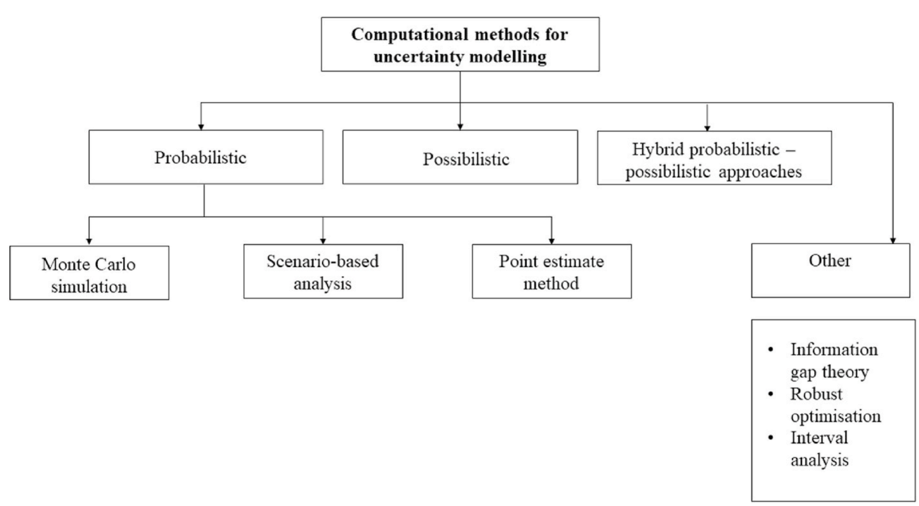


Fig. 6. Categorisation of computational methods for uncertainty modelling. Source: reproduced based on the categorisation by Ref. [14].

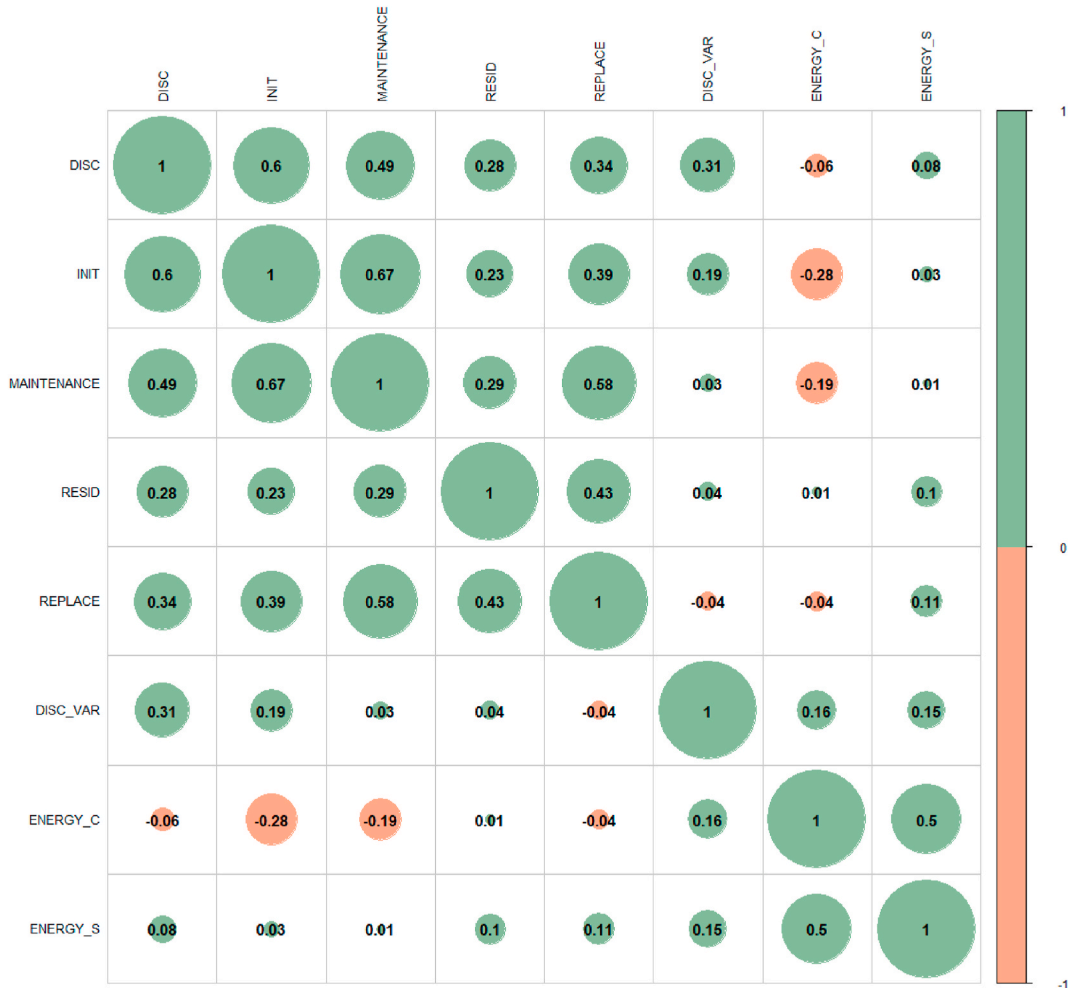
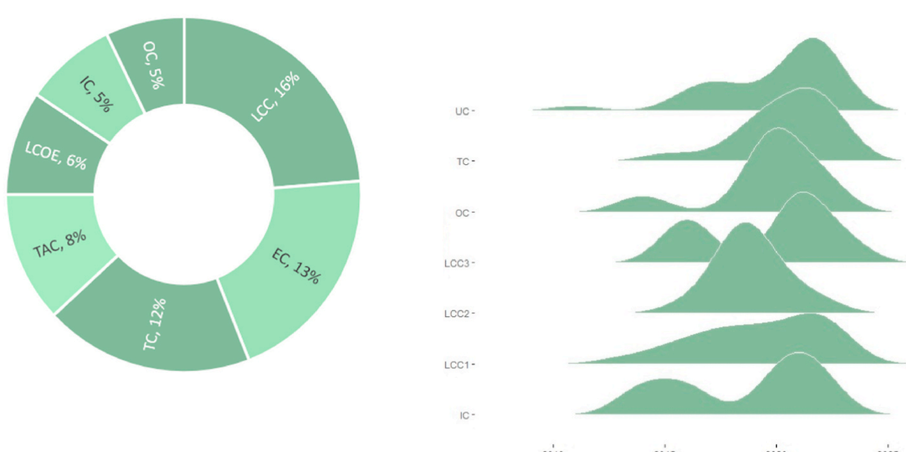


Fig. 7. Correlation matrix of LCC components considered in reviewed studies. Source: Compiled by authors, based on classification by [15].



(a) (b)

Fig. 8. Most used approaches for cost modelling, in percentages (a), and over the years (b). Note: "Other" merics include (O&M, EC), ACSR, COE, GC, (IC, O&M), (LCC, EC), NPC, (OC, EC), PBP, SPB, ACS, (ACSR, CvaR), AEC, ATLCC, (COE, NPC), (DPB, NPV), EAC, Exergy, (GPC, NPV), (IC, MC), (LCC, DPB, NPV, LCOE), (LCC, IC), (LCC, LCOE), (LCOE, IC), (LCOE, PBP), NTC, O&M, Profit, (TAC, EC), (TC, IC), TCO, TIC.

Table 2
List of research questions to be addressed.

Research Question	Figure	Theme of the figure
RQ1	Fig. 8	Association between cost components
RQ1	Fig. 7	Most used approaches for cost modelling
RQ1, RQ2	Fig. 2	Relative and absolute, and specific cost measures over the years
RQ3	Fig. 3	Climate zone distribution
RQ3	Fig. 4	Association between climate zone and assigned cost metrics
RQ4	Fig. 5	Secondary cost metrics, hybrid generation and government incentives considered in case studies

micro-focused economic objective is being supplemented with macro-economic. Thus, some modellers take into consideration not only replacement costs, but also government incentives, that is, subsidies as in Ko et al. [30], and other incentives related to demand response programs as in Hakimi et al. [127], or regulations, such as emissions costs [86].

Although considering largely the same cost components (capital or initial cost, energy cost [30] or specific imports and exports [67]), as well as government policies, what Ko et al. [30] and Sim and Suh [46] call LCC, Ghorab et al. [86] and Tonellato et al. [67] call TAC, or Murray – TC [63]. This illustrates the widely disparate application of the theoretical cost metric constructs. Also, as important as the inclusion of macroeconomic incentives may be, it nevertheless delimits the generalisation of results, which would otherwise be mostly tied to the climate zone of the case study.

For inclusion and exclusion criteria of cost components when applying LCC, application context matters a great deal. Sharafi et al. [54] focus on generation-source-specific costs and optimise the net present value of LCC, that is, investment, O&M, replacement, and utility costs, accounting also for the rental cost of the land, storage and transportation costs. Still others, such as Hakimi et al. [127], consider the costs related to power interruption. Thus, the specific consideration of some costs and variations of the common LCC depends on the objective of the optimiser.

3.3. Application of discount factor

Typically, to convert the future recurring expenses to the present, costs are discounted and initial costs are amortised taking the year as a basis [30,79,123]. Investment costs [79], more specifically, capital costs [82], but also energy (that is, utility and electricity generation) costs [27,35,123] are annualized, as in principle, all future costs should be discounted to the present. Most frequently, this is done using the equivalent annual cost method [27,35,41,62,79,101]. Consideration of the fuel price escalation rate is a common strategy to factor in the future, though this parameter is set constant in the earlier work of Ko et al. [30].

3.4. Application of constraints to the economic objective function

There are various constraints applied regarding the physical concept of the problem. Energy balance [54,62,82,123], maximum and minimum power and energy [127,137], energy efficiency and production variations [82], as well as production and storage [62,123,151], and, to a lesser extent, available space [30], are relatively common. For countries with lower sun exposure, constraints on sunlight availability have been applied [104]. Similarly, when important, the reliability constraints [101,127], or nZEB constraints on energy consumption and production [123] are applied, and, when batteries are considered, the value of heating in charging and discharging modes are delimited, and demand response for electrical loads is constrained [149].

Economic constraints, such as the payback period, have also been considered [123], although, as discussed later, payback is more commonly used as a primary objective. Also frequent are the macro-economic constraints, such as regulations on RE penetration [30, 62,101], minimum efficiency requirements or maximum emission limits [123], or both lower and upper limits of power output efficiency [149].

At a higher level of aggregation, electricity grid constraints are found to be more important to include for finding feasible optimal solutions [56], or constraints related to user comfort [35]. User comfort more commonly enters the multi-objective optimisation problem through a separate objective. However, various articles do not consider constraints explicitly [29,108].

3.5. Application of relative cost measures

In addition to LCC, relative measures, such as LCOE, that is, LCC divided by the energy generated over the project lifetime, have been applied (see Fig. 2a). Albeit minor, the application of relative measures allows for the evaluation of different projects when the electricity generation aspect is important (for example in smart grid-connected buildings [93]). Similarly, LCOE has also been applied in a more detailed way. The detail has been added by incorporating local regulations: feed-in tariff subsidy, transmission loss and network expansion saving, and carbon reduction benefit [93].

A similar measure to LCOE considering the cost per energy unit generated is the COE measuring the cost per energy served [101]. Again, not only the capital, and O&M but also replacement costs and fuel costs are taken into account.

Yet another relative metric is the ACSR, which has been applied in recent years to evaluate the saving rate of the renewable energy-driven system in comparison to the base scenario [104]. This measure has also been applied when determining optimal device capacities [102] or finding an effective hybridisation of solar and wind sources [104].

3.6. Application of specific cost measures

Simplifying the notion of LCC, other studies only consider initial costs and energy costs [27,35,41,56]. This is done in cases of a higher level of abstraction – when considering distributed energy system performance [56], when modelling for costs with division into two stages whereby there is uncertainty in the second stage [62], or when modelling an nZEB where economic and environmental factors are relatively less important, as more importance is given to the social aspect [41]. Peculiarities of the case study macroeconomic conditions, such as energy price subsidisation rates, and step utility tariffs also make energy costs more important to address [27]. Some studies consider energy costs alone [121] when the concern is the demand-side management, in particular, scheduling of appliances.

3.6.1. Initial and operating costs

Initial capital costs and operating costs whereby operating costs comprise fuel cost, maintenance cost, electricity purchasing cost and profit from the feed-in tariff [82] expand the previous concern with solely initial and energy costs.

3.6.2. Leading the way: operating costs on the rise

Somewhat later, a research stream concerning specifically the operating costs develops (see Fig. 2b); interest in variable energy prices in an attempt to minimise the primary energy usage has developed [151]. This latency is perhaps due to the fact that earlier studies find the appreciation of variable energy prices meaningful only following the cost minimisation criterion, and not the energy-saving one, showing the changes in the relative importance of initial and subsequent costs during the period of studies reviewed.

As to operating cost focus, approaches for economic objective optimisation considering variable electricity prices at peak, off-peak and mid-peak hours [108], or the total energy cost, subtracting the total disutility cost due to delayed appliance operations [60], have been

Table 3
Summary of metrics identified in the studies.

Original Metric Group	Variation (s)	Definition	Def. Source	Limitations	Ref.
Absolute Metrics					
LCC		All costs incurred pre-, during and post-production stages.	[26]	•does not consider how fast the return on investment occurs [27] • • hard to obtain the data for oversimplifies project context (i.e., risks, interest rates) [28]	[3,4,29–51]
	NPC	The cost incurred during the lifetime, and income gained, determined by replacement, maintenance, and capital costs, fuel costs.	[52,53]		[52–54]
	NPV	Difference between the present value of cash inflows and outflows over a period of time.	[49]		[27,49]
TC		The sum of capital and O&M expenses.	[55]	• does not consider how fast the return on investment occurs [27] • total depends on the judgement of the researcher	[55–70]
	ACS	Annualized capital cost, annualized replacement cost and annualized maintenance cost.	[71]		[71]
	ATLCC	The sum of the annuity of investment costs, O&M, replacement, negative residual value, feed-out grid costs and generated income through electricity feed-in tariffs.	[72]		[72]
	EAC	Investment, fuel, energy integration, O&M and revenues from selling, tax deduction and credits.	[73]		[73]
	GC	All relevant prices excluding all applicable taxes, VAT, charges and subsidies	[74]		[75,76]
	NTC	The sum of different prices of capital, O&M, replacement, and energy expenses	[77]		[77]
	TAC	The sum of investment costs and operational costs.	[78]		[78–88]
	TCO	The sum of capital, O&M, replacement, energy expenses	[89]		[89]
Relative Metrics					
LCOE		LCC by a unit of energy	[90]	• oversimplifies project context (i.e., risks, interest rates) [28] • has difficulty representing distributed systems due to differences in rates of efficiency improvements and load [28]	[47,49,90–98, 98,99]
	COE	LCC by a unit of energy	[100]		[53,100,101]
ACSR		The relative difference between reference and improved energy system	[102]	• does not account for the total cost	[102–105]
Exergy		The physical cost of products of energy systems and their associated waste	[106]	• difficult to calculate (requires extensive data)	[107]
Specific costs					
EC					[36,37,39,78, 108–122]
	AEC				[123]
IC					[76,99, 124–132]
	TIC				[133]
OC					[134–139]
	O&M				[140]
Combination of specific costs					[100, 141–150]
Other absolute metrics					
PBP		Time required to recover the initial investment.	[49]	• ignores time value of money (except DPB) and possible profitability of the project	[5,6,98]
	DPB	Initial cost of investment divided by the net savings.	[49]		[27,49]
	SPB	Ratio of extra cost to the savings.	[151]		[151,152]
CVaR		Expected average value of the distribution value that is lower (or higher) than a fixed percentile.	[103]	• only calculates the riskiness • depends on the risk definition/aversion of the researcher	[103]
Profit		Revenue less the cost.	[153]	• does not consider when the profit occurs • ignores the time value of money	[153]

Although other specific cost combinations are indicated in a separate column due to the high frequency, such approach is not taken in other original metric groups (when several metrics have been use, their work is cited in Ref. column in various groups). Thus, in this table, no distinction is made between one objective comprised of several specific cost groups, or several objectives (secondary metrics).

adopted. Subsequent studies simultaneously examine operating costs, emissions, and the peak-to-average ratio [137]. With the rise of demand response programs, some recent models highlight the hybrid demand response cost for flexible electrical and thermal consumers [149].

3.7. Application of a payback period

Although payback period is much less common, four from selected studies considered it as the only metric, and two more considered it as a supplementary metric in conjunction with net present value-based cost analysis [98] and as part of a larger selection of representative metrics (LCC, NPV, LCOE) [149]. Payback methods are especially important in economically volatile conditions, as they allow to assess and mitigate risks [27]. However, the country cases where PBP is applied comprise a wide variety of economic conditions from high-income, developed and, as a consequence and source, stable economies [154] (Italy, Australia, China, N = 5, 83 %), to lower-middle income economies (Iran N = 1, 17 %) [17]. Indeed, the distribution of the payback method over development level is concentrated on the lower development levels than the overall distribution of selected studies, and, therefore, it can be concluded that some methods are applied relatively more in unstable or less developed economies.

3.8. Climate zones and development levels in case studies

Regarding the climate zone (for the full list, see Table 4) distribution of case studies, most case studies are conducted in Csa (emperate climate with dry, hot summers, 22.76 %), followed by Cfb (temperate climate with no dry season and warm summer, 13.01 %), and Dfb (continental climate with no dry season and warm summer, 10.57 %). The distribution of case study climate zones is plotted in Fig. 3.

The associations between climate zones and multi-objective optimisation objectives are negligible, but TC and climate zone B are slightly associated (0.27), just as are LCC1 and climate zone D.

However, from Fig. 4, one can conclude that associations are low, and therefore, that there is no pattern detected for research in specific climate zones to favour the inclusion of specific cost components. This signifies that cost component inclusion is rather objective, and possibly, more uniform rules can be applied by policy makers if any optimisation procedures are carried out, or best practices are developed.

3.9. Modelling for hybrid generation

Only 48 (37.21 %) of all selected studies have both wind and solar installed for energy generation. The hybrid generation in studies does not seem to have any upward trend. Instead, there may be a slight decline (see Fig. 5a).

There is a low correlation between hybrid generation (wind and solar) and climate. As for hybrid generation and cost components, the association is again negligible showing that the existence of a mix of generation technologies is weakly related to the choice of the metric.

Table 4
Köppen - Geiger climate zones.

Zone (1st)		Sub-zone (2nd)		Subzone (3rd)	
A	Tropical	F	Rainforest		
		M	Monsoon		
		W	Savanna, dry winter		
		S	Savanna, dry summer		
B	Dry	W	Arid deser	H	Hot
		S	Semi-arid or steppe	K	Cold
		W	Dry winter	A	Hot summer
C	Temperate	F	No dry season	B	Warm summer
		S	Dry summer	C	Cold summer
D	Continental	W	Dry winter	A	Hot summer
		F	No dry season	B	Warm summer
		S	Dry summer	C	Cold summer
				D	Very cold winter
E	Polar			T	Tundra
				F	Ice cap

Source [18].

Table 5
List of influential articles.

Ref.	Journal	Country (case)	Year	Metric (original)
[123]	European Transactions on Electrical Power	USA	2011	AEC
[29]	Applied Energy	Sweden	2013	LCC
[104]	Applied Thermal Engineering	Italy	2014	SPB
[30]	Energies	South Korea	2015	LCC
[54]	Renewable Energy	Canada	2015	NPC
[108]	Neurocomputing	*NA*	2016	EC
[56]	Applied Energy	Switzerland	2016	TC
[125]	Applied Energy	Italy	2016	TC, IC
[79]	Applied Energy	Switzerland	2017	TAC
[60]	Energy Efficiency	*NA*	2017	TC
[35]	Journal of Building Engineering	Lebanon, France	2018	LCC
[62]	Applied Energy	Switzerland	2018	TC
[127]	IET Renewable Power Generation	Iran	2019	IC
[41]	Sustainable Cities and Society	Singapore	2019	LCC
[82]	Energy Conversion and Management	China	2020	TAC
[93]	Energy Conversion and Management	China	2020	LCOE
[101]	Energy	Algeria	2020	COE
[137]	Sustainable Cities and Society	*NA*	2021	OC
[86]	Applied Sciences	Korea	2022	TAC
[27]	Journal of Building Engineering	Iran	2022	DPB, NPV
[149]	Sustainable Cities and Society	*NA*	2022	O&M, EC
[121]	IET Smart Grid	*NA*	2022	EC
[104]	Journal of Energy Storage	Sweden	2023	ACSR

Note: country listed is (are) the country(-ies) of the case study, and not necessarily of the authors' intitutions.
Note 2: *NA* denotes "not added" in the article.

3.10. Consideration of government incentives

Government incentives and regulations (such as grants, or emissions market; note that we do not collect data for pricing mechanisms (i.e., subsidised tariff rates)) have been considered relatively more often in the early studies; the later studies consider them equally or less often in the recent years (see Fig. 5c). Overall, only 11.63 % (N = 15) of selected studies consider government incentives, making any trends hard to detect.

3.11. Use of secondary or supplementary cost metrics

Secondary metrics have been rising in popularity (see Fig. 5b). To classify a study considering a secondary method, authors must have stated that various metrics have been analysed separately, that is, they enter the optimisation problem as separate objectives.

The first attempts to combine different metrics include both types of metrics – the absolute (investment cost), and the relative costs: energy-specific (difference in primary energy consumption) and total (global) cost [125]. Although the majority of studies consider two separate metrics (N = 9, 81.82 %) [49], consider four. Two separate metrics may include the overall cost metric (TAC, NPV, NPC) and energy costs (EC, COE, also GPC) specifically [48,73,141]. Alternatively, it may consider TC [125], or total relative costs concerning energy (LCOE) [153] in conjunction with investment costs. Other studies focus on the total cost metric (i.e., LCC, NPV) and supplement it with the relative costs (LCOE) [47] or discounted payback period [27], or only consider the relative costs (LCOE) and payback period [98]. Still, Wijeratne et al. [49] make a strong case for economic objectives using four metrics, when optimising building integrated photovoltaics roof projects in the early design phase, and [103] considers the risks involved, considering ACSR with CVaR.

3.12. Consideration of uncertainty and risk

Considering costs alone when planning for or managing an existing project, may be insufficient, as even the overall relative cost measures, such as LCOE, oversimplify project context, ignoring project risks and interest rates, as well as other elements of the costs of capital [28]. Therefore, in case information on decision outcomes and their probabilities of occurrences are known, one may wish to model for risk; if the outcomes and/or their probabilities are unknown, uncertainty arises [155]. To investigate uncertainty in a model, sensitivity analysis (identifying main drivers of output variation) and uncertainty analysis (identifying the differences in optimal designs when uncertain parameters take on different values or scenarios) can be applied [62].

However, uncertainty is considered sparingly: in titles, "risk" and "uncertainty" are mentioned only two and six times, respectively; "stochastic" has three mentions, while "fuzzy" has two, together yielding 11 unique articles which consider these terms as principal. Uncertainty is modelled throughout the years, but the risk studies appear only recently, in 2021 and 2022.

Sources of uncertainty can be divided into technical (operational, as load and generation, and topological, as a line or generator outage), and economic (macroeconomic, as inflation rate, growth rate, income level and unemployment, regulations, and microeconomic, as uncertainty in fuel supply) [156]. Indeed, data, such as demand and price projections, used to be incomplete, imprecise, or vague and used to be hardly available as deterministic data [157]. With smart metering on the rise, this may not be the case in future given that the regulatory framework is adapted to make data interoperable, that is, to be shared and used by different agents [158]. Stochastic uncertainties due to system and environmental variations (loads, wind power generation, photovoltaic power generation) must be accounted for as well. Hereafter, the authors consider the economic uncertainties only.

When forecasting, deterministic or uncertainty modelling approaches can be applied. Deterministic forecast refers to a single-point prediction result, the expectation of future power from a mathematical point of view [159]. Some early works use this approach, estimating technical parameter uncertainty with a method of moments [90]. This approach has been shown to yield significant deviations of estimates, more specifically, underestimation of the total cost [62], when compared to the probabilistic stochastic approach.

Computational approaches for uncertainty modelling (see Fig. 6) can be divided into probabilistic, possibilistic, and hybrid-possibilistic [14]. Probabilistic forecasting is expected to be important in RE power forecasting [160]. It includes both parametric and non-parametric methods, depending on whether the distribution of single-point prediction error is assumed in advance. The secan be modelled both with simulation (i.e. Monte Carlo) and analytical methods (i.e. point estimate). Thus, the two most common probabilistic forecasting approaches – scenario forecasting and Monte Carlo simulation – can be either parametric or non-parametric. To analyse probabilistic power system stability, first uncertain input variables (operational and disturbance) and operating conditions must be modelled. Afterwards, computational methods can be applied, and stability indices calculated.

As previously stated, parametric probabilistic computational methods assume certain probability distributions. For economic parameters, such as price and income, the log-normal probability distribution is preferred [14].

The most common approach is to use probabilistic scenarios when representing uncertainty in such economic parameters as energy prices [62,82], but Markov decision process been applied as well [161].

However, only a fraction of studies considers economic uncertainties. More precisely, from the selected studies, two of which have "uncertainty" in the title (N = 6), consider economic uncertainty.

None of the selected studies considers possibilistic methods or hybrid probabilistic-possibilistic methods for uncertain economic variables. Other methods, such as information gap theory, robust optimisation, and interval analysis, are also not applied in selected studies.

4. Cost function component analysis

Regarding the cost function components, Fig. 7 shows the correlation matrix of LCC components considered in the reviewed studies. Evidently, initial investment costs are correlated with operational – maintenance (0.67) and replacement (0.39) – costs and are usually discounted (0.60). When discounting, the inclusion of fuel escalation and inflation rates has a low correlation with initial investment (0.31); this choice does not seem to correlate with the other cost components. On the other hand, the residual value and replacement are correlated to a larger extent (0.39). In the studies which model the energy imports from the grid, it is less likely (−0.30) to consider the initial investment costs, and their discounted values (−0.28), as well as the maintenance of the equipment (−0.19). This indicates that, firstly, the investment and operational costs, which are then discounted, and secondly, the utility costs, in which case the initial investment is abstracted from, are the two main streams of cost function modelling. For coherent categorisation purposes, the major cost metrics were re-defined as in Table 6.

The proposed categorisation, including 92.24 % (N = 119) of selected studies (after exclusion), is flexible and based on components of LCC considered in the cost functions. The components considered in the cost categories are not exclusive to the category.

The economic efficiency of EC accounting delimits the granularity of consumption measuring [11]. Therefore, various metrics have been applied. Regarding the original metrics named by the studies, there is a great variety of approaches considered. Fig. 8a shows the popularity of the most frequently used cost metrics of all selected studies named by authors, that is, LCC (15.5 %), EC (13.18 %) and TC (12.4 %), followed by TAC (9.1 %), LCOE (6.2 %), IC (5.43 %) and OC (4.65 %). Fig. 8b shows the distribution of the main assigned metrics over the years.

The proposed categorisation based on cost components overlaps 44.54 % (in the case of only assigned studies) or 41.09 %, when considering all selected studies. In particular, considering all selected studies and having the author-assigned metrics for basis, the overlap rate for all LCC metrics is 88.00 %, TC – 27.27 %, OC – 14.29 %, UC – 100 %, and IC – 71.43 % Again, to justify the relatively low overlap rates, it must be reminded that the assigned metrics are not exclusive, and studies often define their metrics as a mix of the assigned metrics, in which case they may not be considered as overlapping. It also must be noted that when calculating the overlap, the assigned metrics are linked to original metrics named by author, whereby original metrics are LCC (included in the study), TC (exact TC or variation thereof, as specified in Table 3, included in the study), OC (OC or O&M as the primary metric of the study), EC (EC as the primary metric of the study, linked to assigned UC), IC (as the primary metric of the study).

Regarding cost metric comprehensiveness, the average originally named LCC considering study only takes into account 4.92, but TC – only 4.21 LCC cost components of nine (see the component list in Table 4).

The popularity of total costs and energy costs, as shown in Fig. 8a, that is, LCC, TC and TAC, against specific EC, is also evident when disaggregating the assigned LCC metrics (LCC1, LCC2 and LCC3) to show which cost components are primarily used; it appears to be initial (100 %), maintenance (82.28 %) and energy import costs (78.48 %), showing the preoccupation with initial costs and consumed energy costs, as well as the neglect of residual costs (20.25 %). When disaggregating TC, a similar picture appears; initial (100 %) and maintenance (100 %) costs are always considered, and energy import costs come next to it (68.57 %). In this case, none of the studies considers residual costs.

Thus, one can conclude that investment (to large part initial) costs, maintenance and energy costs are the most important cost components of overall assigned cost metrics. However, the assigned metrics only overlap to some extent; when the authors' original metrics are considered, the same conclusions can be drawn.

Table 6
Re-categorised cost metrics.

	Investment cost		Operation cost		Utility cost		Others			Occurrences	
	Initial investment	Residual value	Maintenance	Replacement	Energy consumed	Energy sold	Discounted	Uncertainty	Incentives		
IC	✓	(✓)	×	×	×	×	(✓)	×	(✓)	5	4 %
OC	×	×	✓	(✓)	(✓)	(✓)	×	×	(✓)	8	8 %
UC	×	×	×	×	✓	(✓)	(✓)	×	(✓)	27	27 %
TC	✓	×	✓	(✓)	×	×	✓	×	×	35	35 %
LCC1	✓	(✓)	✓	(✓)	✓	(✓)	(✓)	(✓)	(✓)	24	24 %
LCC2	✓	(✓)	×	×	✓	(✓)	(✓)	(✓)	(✓)	14	14 %
LCC3	✓	(✓)	✓	(✓)	×	×	(✓)	(✓)	(✓)	6	6 %

Note: (✓) means the LCC component may or may not be assigned for the metric.

5. Discussion

The study collected information from selected articles that optimise the costs within a multi-objective optimisation problem for buildings with renewable energy. The cost functions were studied, and overall study objectives and case study environmental and macroeconomic factors were collected to analyse their associations with cost objectives. This review attempted to answer four questions: What cost metrics and components thereof are primarily used? How can these approaches be grouped? How do macroeconomic and climate conditions are associated with cost metrics? And, lastly, what are the dynamics of the application of cost objectives?

5.1. Cost metrics and components

Answering RQ1, it was found that majorly LCC, EC, TC, and TAC are applied, followed by LCOE and IC. When assigned new metric names based on the cost components, it appears that absolute total metrics, such as LCC and TC, also focus on initial costs and imported energy costs, and to a lesser extent – exported energy costs.

This highlights the developments in the last decade in global LCOE from newly commissioned RE projects to have fallen considerably; in effect, renewables are now the cheapest power option in most regions [2]. This is a relatively recent improvement from 2018 [162] when RE scenarios were more expensive, now making the difference between imported energy costs from the grid and self-generation starker year by year.

As for investment costs, the authors of this study distinguish between initial costs borne by the private sector, and government incentives, which usually enter cost objective function separately as one-time subsidies (i.e., in building retrofit) or as ongoing (subsidised) tariff rates within the grid import (export) cost (income) component, to name the two most common modelling approaches. Most studies overlook the government incentives, especially those of one-time payments, reflecting the funding structure to be skewed towards private investments (in 2019, it accounted for 80 % of total energy investment, in 2013–2018 being led by project developers themselves [163]). However, public financing will need to double in 2021–2030, and tailored pricing instruments, as net billing and net metering, would support distributed power generation; tax incentives, subsidies and grants would complement regulatory and pricing mechanisms [1].

These findings are significant to the distributed grid studies, as these allow us to reflect on the cost metrics currently used (or neglected), and adapt them to aid decision-making in the future, considering also the public investments, which will rise in relative importance. This, in turn, is relevant also for decision-makers in the public sector, to tailor the pricing mechanisms and regulations for buildings with RE generation. Given the importance of public investment in distributed generation, in the future, public incentives should be considered with greater granularity. To the best of the author's knowledge, this remains a yet unexplored field on an aggregate level.

5.2. Cost objective approaches

Answering RQ2 we partly follow the common division of investment valuation approaches, and divide the cost objective approaches into discounted cash flows (absolute metrics), relative valuation (cross-sectional, or comparing to a unit of energy produced), as well as add to these major approaches the absolute specific costs (such as IC, EC). We do not review any study with a real options approach, or options pricing approach for that matter.

While this division is not new, its application of it is. The authors do not find any previous studies categorising the cost approaches for buildings with RE. The application of relative measures is minor. Although the share of relative measures is rising, the majority of studies employ absolute measures instead.

This may signify that, in general, there is enough data to perform a full analysis of costs. However, methods such as model transfer method may augment available data for optimisation problem [164]. Overall, data availability is not of concern, as relative cost metrics (cross-sectional) require less data. However, it must be noted that an average study optimising LCC or TC only considers less than five cost components of nine. Given this, the absolute cost metrics are not always representative of the life cycle approach, and it can be concluded that in a multi-optimisation problem setting, cost objectives may take an absolute approach due to other objectives balancing out the energy and environmental objectives.

5.3. Development, climate, generation and the cost modelling choice

Regarding RQ3, the study found a low association between climate zone, hybrid generation, and cost metric assigned, based on which cost components are considered. This suggests that there is a great variety of projects in most climate zones, and there is no association between the major project types.

Moreover, the assigned cost metric does not seem to be associated with hybrid generation. Perhaps, the difficulty to bring out any pattern is due to the small size of studies considering hybrid wind-solar generation ($N = 48$). However, considering a mix of solar-wind generation sources for buildings is roughly constant. On an aggregate level, there is a need for stability in RE power generation, as it increases in importance in the total energy mix. It has been confirmed that the stability of single wind or solar generation source is related to its generation capacity. Thus, variability decreases as aggregated area size increases, and strong promotion of regional cooperation may aid the further reduction of operation costs [165].

While these findings are not significant, they may allow us to conclude that the current research is not biased towards some metrics when specific climate zones are considered, although this may be the case with development levels.

When considering the development level of the country, some methods (PBP) are distributed over the lower development levels. The reasons for the PBP have been brought out by Ref. [27]: market volatility pushes project managers to use these methods, as these allow for risk assessment and mitigation. Existent research on emerging country investment valuation, however, does not suggest that payback, and discounted payback, are the most popular methods [166,167], and this study is limited in its exploration of this area as well. Thus, future research may study the investment in RE-powered buildings, in particular, the valuation method differences between the countries with different levels of macroeconomic volatility.

5.4. Recent dynamics, trends and future of cost objective modelling

Regarding RQ4, a recent rise in secondary metrics has been observed. However, it only reached around 12 % in 2022. This choice to supplement the overall costs with specific energy costs allows to disaggregate the costs but does not allow to identify the main cost contributors, as the objectives enter the optimisation separately.

For many companies, wind and solar investments are low-volatility investments [168]. However, uncertainties about a generation (solar irradiation, wind speed), and macroeconomic environment, such as price fluctuations of fuels and imported electricity, bring about uncertainty. Moreover, regional requirements and policies may increase uncertainty [11]. The impact of uncertainties on cost optimisation is manifold: cost of energy may increase if uncertainty on the forecast on production, consumption and energy price is present; buildings may fall short on energy supply commitments, and unstable control systems may increase energy cost and inconvenience for users [10]. Consequently, the consideration of policy uncertainty effects on the microeconomic level is a highly relevant future avenue of research. Recent studies suggest that on the macroeconomic level, monetary and fiscal policy uncertainty have opposite effects on RE production, with the first having a negative effect; trade policy uncertainty has no effect [169].

To tackle the uncertainty in economic parameters, as the price on the microeconomic level, or income and inflation on the macroeconomic level among other uncertain parameters, probabilistic, possibilistic or hybrid computational methods can be applied, but authors find them to be used sparingly, though constantly throughout the years. Studies mainly model uncertainties of technical parameters, mostly power generation. This conclusion, however, is limited to the analysis of studies which have mentioned uncertainties in titles. A growing concern is a correlation, and dependence between power system uncertainties, but none of the selected studies (and most works in general) address a dependence between uncertain inputs [14].

Moreover, uncertainty can be tackled by considering the options of a manager. As early as 2017 [35] it has been recognized that investment decision builds upon the priorities of the decision-maker: whether to save directly during initial investments or wait for profits to come about. It has also been suggested that traditional project evaluation techniques alone are insufficient in face of the deregulated energy sector to deal with the additional risk and uncertainty [170]. The role of management decision-making, however, has been neglected by all selected studies, but this is not the case in the RE field overall (i.e. [171]). However, critics hold that in most cases, real options are not directly applicable to an investment in energy systems, and require taking into account its physical characteristics [172].

6. Conclusions and future work

While the cost per energy produced from RE sources fell in the recent decade and RE is now the most feasible alternative to capacity additions in most world regions [1], there is a lack of secondary research addressing cost objectives that intersects at the nexus of RE source (which have a fundamentally different cost structure) powered buildings (which consume around 30 % of global final energy), and MOO (the recent advances in optimisation). In particular, the reviews are tackling the RE generation in buildings (i.e., [166]) extensively, as well as MOO for RE (for solar, see Ref. [173]), and MOO in buildings (i.e., building energy systems [174]), not necessarily joining the three themes with a focus on costs. This is indeed problematic, as prices are important indicators of the information available in the market given that markets are efficient. This study aims to close the research gap, carrying out a semi-systematic literature review to identify the cost components considered in the existing research, and categorising them into new cost metric groups. Considering different development levels, and therefore – implicitly – also frictions in markets, authors explore the possible differences in the cost metrics applied relative to country development level and climate zone. Lastly, recent trends in cost metric applications are outlined.

Regarding the cost components (RQ1), initial costs (N = 91, 70.5 %) and energy import (N = 100, 77.5 %) costs are used most frequently, but the average study originally named LCC only considers 4.92 of nine cost components. Therefore, based on cost components, the cost metrics were re-categorised and yielded the same result: initial and energy import costs are the most common.

The original cost metrics can be grouped (RQ2) according to the comprehensiveness of the costs considered over the project lifetime and the calculation of absolute or relative costs incurred. Regarding the comprehensive measures, such as LCC, models have progressed in both ways – by simplifying, and by expanding in cost comprehensiveness including also the macroeconomic environment. As the optimisation problem must be constrained, constraints are applied, but are in nature mostly technical; economic constraints, such as the payback period, are rare.

Regarding development level and climate zone (RQ3), only studies considering initial costs and energy costs differ significantly in their variances when development level is the dependent variable. The associations between climate zones and MOO objectives are negligible, as are the associations between climate zones and specific cost components.

Regarding recent trends (RQ4), secondary metrics have been rising in popularity. Although not to a large extent, uncertainty has nevertheless been modelled throughout the years. Risk studies appear only recently.

The study suffers several problems regarding the methodology: the Scopus website is assumed to be representative of the research field, and grey literature is thus neglected. This may impact the results so that the findings do not reflect less established innovative methods which may be harder to publish in peer-reviewed journals. For practitioners, this means that the cost analysis methods suggested herein may be too conservative for the real-life applications.

The authors believe that the major drawbacks of the currently applied economic objectives are the partial neglect of managerial flexibility in investment projects. Therefore, in the case of RE project appraisal, transitioning from a cost-accounting perspective towards a managerial accounting perspective would be appreciated. This can be done by supplementing the primary metrics with secondary cost metrics, and/or a real options approach (i.e., an option to delay investment). Supplementing cost metrics provides a better understanding of project costs and risks, but still wouldn't allow for investments to be reversible, cash-flows to be uncertain, and considers management to be passive [172]. Real options can then aid in modelling for the aforementioned drawbacks with discounted cash flow metrics.

As a future work, it is suggested to consider the uncertainty. On relatively immediate individual project level, with large uncertainty there is a large risk of predicted energy-related objective would not be fully realised, or financial resources to be partially wasted [175]. Regarding uncertainties on an aggregate level on medium-term, the uncertainty of climate policy introduction is a major characteristic of financial risk [176].

Moreover, in the future, the valuation methods and differences thereof could be compared for buildings with RE between the countries with different levels of macroeconomic volatility. As a first step, research more economically volatile country setting should be done to characterise and contrast the objective measure choice with respect to the market volatility. Currently influential articles concern mostly high-income or developed countries, yet the smart grids are expected to spread in the less developed countries as countries decarbonize, digitalize and decentralize, although the progress with grid modernization still ongoing in developing world [177].

Furthermore, cost objective could be expanded considering the social aspect as well – it has been proposed to include not only techno-economic and environmental, but also socio-economic dimensions when evaluating the projects [178]. Social aspect is considered, for instance, in Ref. [179] when choosing the optimal solution for water-heating system, but application for RE-powered buildings generally is rather scarce.

Lastly, it must be remembered that not only economic objectives, but also non-economic objectives are important to address the general inquiry on how to incentivise the energy-efficiency related decisions [180]. Therefore, modelling for non-economic goals should be continued.

Author statement

Anna Auza: Conceptualization; Data curation; Investigation; Methodology; Roles/Writing - original draft; Ehsan Asadi: Conceptualization; Methodology; Project administration; Resources; Supervision; Review & Editing. Behrang Chenari: Conceptualization; Investigation; Methodology; Resources; Review & Editing. Manuel Gameiro da Silva: Supervision; Review & Editing.

Declaration of competing interest

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Data availability

Data will be made available on request.

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