A Review of the Coherence of Strategies to Optimize Photovoltaic Systems within the Built Environment in Nordic Countries

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Abstract

Climate change is often cited in renewable energy research by stating motives in environmental, technical, social, and economic categories, which can be linked to metrics that are called key performance indicators (KPIs). Furthermore, these indicators can be set as a target for an optimization model and become optimization objectives. This paper critically reviews the motives, optimization objectives, and KPIs selected in studies of solar photovoltaic (PV) systems with energy storage within the built environment in Nordic countries. A subset of 36 scientific articles, sorted as relevant from a selection of 349, was analyzed to make the review. The results reveal that even when environmental motives are expressed by 75% of the authors, only 8% focus on optimizing with environmental indicators. This imbalance suggests that the environmental problems intended to be addressed with the optimization model could be left unchanged or even exacerbated by the strategic choices made during the energy modeling. In addition to this, there is a lack of consistency in the way the different indicators are calculated, especially for environmental indicators where the impacts of materials and manufacturing were not included. Furthermore, in the economic and technical categories, the economic volatility and peak power motives do not have a matching indicator within the articles analyzed. Therefore, it is recommended to conduct comprehensive optimization studies that align with carefully considered motives.

Keywords: photovoltaic, optimization, key performance indicators, Nordic

1. Introduction

The decision to invest in renewable energy technologies, including PV, has different motives behind it. According to Bergek and Mignon (2017) the most significant factors are environmental concerns, interest in technology, access to renewable resources, and economic benefits. In their study, the survey participants assessed the environmental benefit with the highest importance. Similarly, the individual motives and decision paths of residential energy supply systems have been studied by Matschegg et al. (2023). Their results show that more than 90% of survey respondents had technical motives. Environmental performance was also highly valued, whereas financial aspects were considered less important. To aim for motives, they can be related to indicators which can be set as targets for performance.

A useful way to improve the performance of an energy system is to use optimization (Lund, 2018). An optimization process is used to identify the best possible solution to a mathematical problem (to determine the maximum or minimum value achievable for a function). This can be applied to both the design and operation of an energy system (Xu et al., 2020). During the design phase, it can determine the optimal capacities and configurations of various subsystems. In the operational phase, it coordinates energy flows between subsystems, such as PV and energy storage systems. A review of the optimization process in planning PV and battery systems was performed by Khezri et al. (2022), they focused on methods including the optimization function (objectives) and constraints. These are the variables selected to be part of the optimization method.

Other reviews of metrics for evaluating the performance of energy systems refer to key performance indicators (KPIs), a metric whose performance is evaluated regarding some objective (Costa et al., 2019). For example, a review

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of KPIs for PV systems with storage was performed by (Kourkoumpas et al., 2018) and gives a detailed description of environmental and energy KPIs, grouped according to the interests of different stakeholders. One of their conclusions was the need for replicable and scalable environmental and energy performance indicators. Another review of the optimization of energy systems by Klemm and Wiese (2022) published a set of indicators for optimizing sustainable urban energy systems. In that study, the main conclusion is the recommendation of multi-criteria optimization approaches.

This set of decisions, which includes motives, optimization objectives, and KPIs can be considered a strategy for optimization. First, the motives are stated. Afterward, the optimization objectives and constraints are defined taking indicators that match the defined motives. Finally, the performance of the optimization process is assessed using KPIs. Despite existing literature on optimization strategies and KPIs for solar PV systems, there is a lack of reviews that standardize the process of defining motives, optimization objectives, and KPIs. Therefore, investigating the coherence between these strategic choices could enhance the effectiveness of results and better align them with stakeholders' interests. In this review, this set of choices made during the optimization process is thus termed the optimization strategic framework, as illustrated in Figure 1.

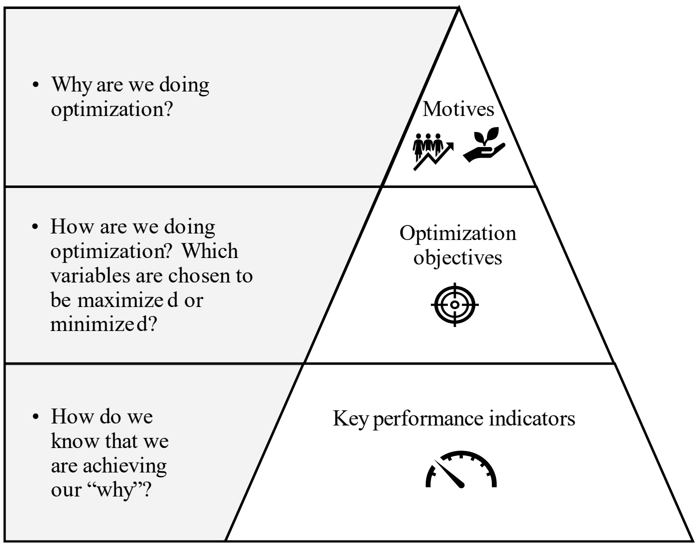

Figure 1. The proposed strategic framework.

The need for this framework is particularly evident in the context of solar PV systems within the built environment in the Nordic countries. Here, solar irradiation is low, and a building's energy consumption is relatively high during winter (Paatero and Lund, 2007). To reconcile this disparity the use of optimized energy systems equipped with storage capabilities is a possible solution (Lund, 2018). In consequence, this review analyzes the indicators and alignment between the motives, optimization objectives, and key performance indicators (KPIs) used in solar PV systems for the built environment within the Nordic countries by aiming to answer the following research questions:

- What indicators are being selected to be used as part of optimization models?
- What is the distribution of the selection of motives, optimization objectives, and KPIs among the environmental, technical, and economic categories?
- Are there matching indicators for the expressed motives?

The focus is on the coherence of the strategic framework presented previously. The analysis is divided into environmental, technical, and economic categories. In the first part, the distribution of choices for the different categories is shown. It is followed by a table with the categories found in each journal paper analyzed. Afterward, a general description of each of the categories of strategic framework plus the mathematic definition of a selection of the indicators found is shown. Finally, the paper discusses current limitations and possible future directions.

2. Method

The analysis uses collected and filtered peer-reviewed journal articles based on the following method. The search engines IEEE Xplore, Scopus, and Web of Science were used to gather scientific articles. The search string used is shown in Figure 2. These searches yielded a total of 349 journal articles. To filter the results, the relevance of each article was assessed by examining the abstract. Specifically, the articles were filtered for the following characteristics: optimization, PV system, built environment, energy storage, and Nordic locations studied. After the sorting process, 36 relevant scientific articles were selected. The graphic summary of the search, filtering, and sorting method is presented in Figure 2.

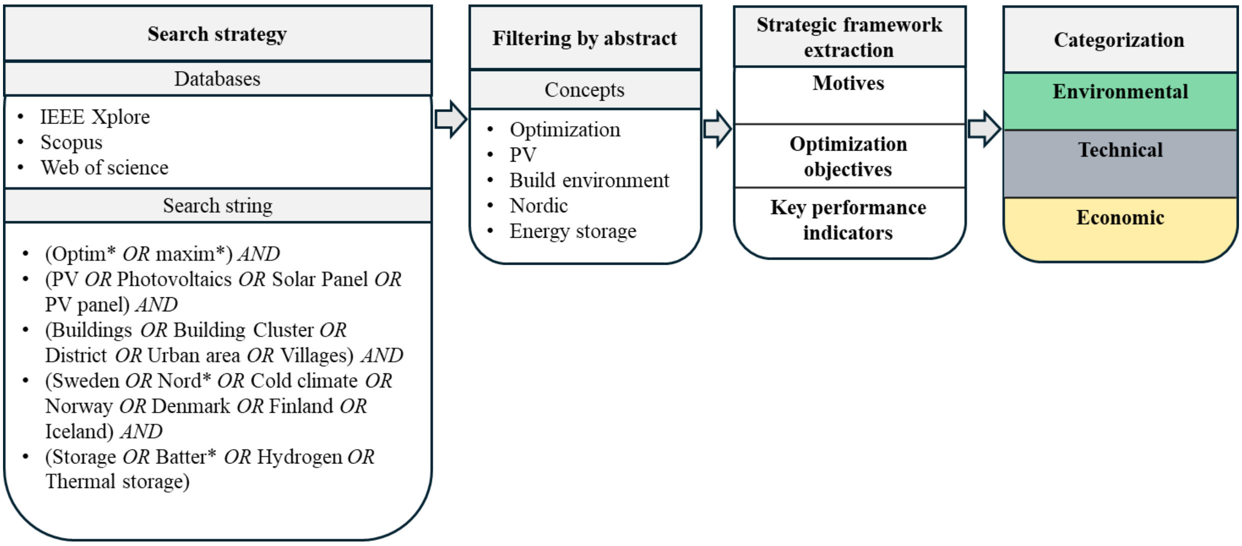

Figure 2. Method for the review.

The selected articles are analyzed based on their optimization strategic framework. Each feature from the strategic frameworks is extracted and assigned into environmental, technical, and economic categories. For this review, the motives refer to the collective goals mentioned by the authors and are extracted from the introduction section of the articles, the optimization objective is typically found in the methodology section and the KPIs are extracted from the results section. In addition, to give a general overview, the percentage of articles that chose a certain category is quantified and compared among the categories.

3. Results

3.1. General distribution of strategic choices per category: environmental, technical, and economic

Figure 3 presents the distribution of various categories across the strategic choices in the analyzed journal articles. Technical motives are prevalent, appearing in over 90% of the studies. Similarly, environmental motives are found in 75% of the articles. In contrast, economic motives are mentioned in less than half of the studies. When it comes to optimization objectives, most articles focus on economic variables, while a small fraction (8%) utilizes environmental optimization objectives. In terms of key performance indicators (KPIs), most scientific articles feature KPIs from the technical and economic categories. However, only 11% of the articles present their results using environmental indicators.

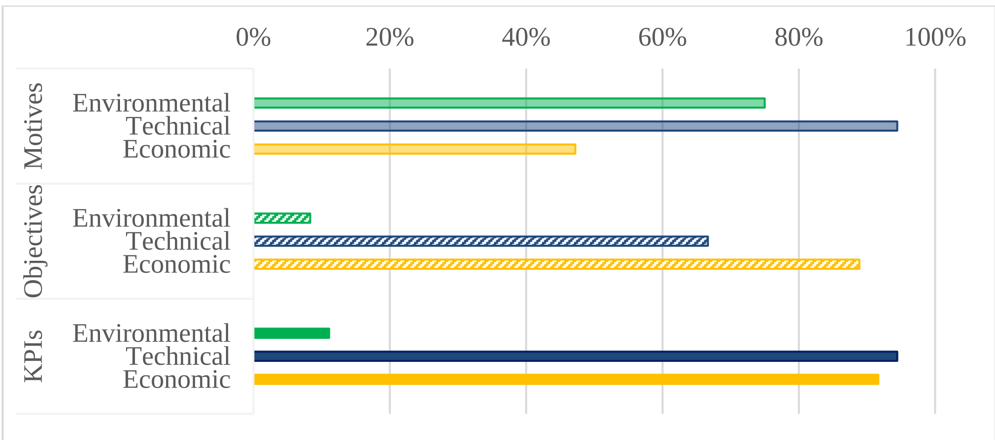

Figure 3. Percentage of articles distributed per strategic choice.

The strategic choices in an individual article are not exclusive to a single category. Table 1 shows that most articles simultaneously demonstrate motives from different categories. Motives as well as objectives from the three above-mentioned categories were studied by Kharseh and Wallbaum (2019). The same was found for the optimization objectives. Environmental, technical, and economic objectives are set in multi-objective optimization models in two studies (Arabkoohsar et al., 2021b; Behzadi and Sadrizadeh, 2023). Similarly, multiple key performance indicators are commonly used in a single study. For example, the results in all environmental, technical, and economic indicators were shown to assess the performance of an optimization for a residential district (Yuan et al., 2022). The strategies used in these articles are complex and comprehensive, built up from multiple individual choices of motives and indicators.

Table 1. The strategic choices in the analyzed articles were distributed per category.

Reference	Environmental			Technical			Economic		
	Mot.	Obj.	KPI	Mot.	Obj.	KPI	Mot.	Obj.	KPI
(Salpakari et al., 2016) , (Hirvonen et al., 2018), (Rehman et al., 2018), (Perera et al., 2019),(Arabkoohsar et al., 2021a)	✓			✓	✓	✓		✓	✓
(Salpakari and Lund, 2016), (Hirvonen et al., 2017), (Hirvonen and Sirén, 2018), (Psimopoulos et al., 2019), (Huang et al., 2019) (Huang et al., 2019), (Mbuwir et al., 2020)				✓	✓	✓		✓	✓
(Nyholm et al., 2016)				✓	✓	✓			
(Nyholm et al., 2016),(Rehman et al., 2019), (Kharseh and Wallbaum, 2019), (Carli et al., 2020), (Srithapon and Månsson, 2023)	✓			✓	✓	✓	✓	✓	✓
(Kharseh and Wallbaum, 2017), (Huang et al., 2020), (Rikkas and Lahdelma, 2021), (Savolainen and Lahdelma, 2022), (Meriläinen, A. et al., 2023), (Meriläinen, Altti et al., 2023)	✓			✓		✓	✓	✓	✓
(Azaza and Wallin, 2017)	✓				✓	✓	✓	✓	✓
(Koskela, J. et al., 2019), (Hajiaghapour-Moghimi et al., 2023)	✓			✓			✓	✓	✓
(Andersen and Lindberg, 2021)	✓	✓		✓		✓		✓	✓
(Rabani et al., 2021), (Fachrizal et al., 2024)	✓			✓	✓	✓			
(Arabkoohsar et al., 2021b), (Behzadi and Sadrizadeh, 2023)	✓	✓	✓	✓	✓	✓	✓	✓	✓
(Fachrizal et al., 2024)	✓			✓		✓		✓	✓
(Goop et al., 2021)						✓	✓	✓	✓
(Huang et al., 2022)	✓			✓	✓	✓			✓
(Yuan et al., 2022)	✓		✓	✓	✓	✓		✓	✓
(Berg et al., 2024)			✓	✓		✓		✓	✓

3.2. Environmental Strategic Framework in the analyzed studies

The environmental category is mainly focused on climate change concerns. Broad expressions of motives, such as “Environmental issues” providing context for an energy-sharing study, are found in some articles (Huang et al., 2022). Another instance of environmental motives is the potential reduction of “Greenhouse gas emissions of buildings by adopting renewable-based hybrid energy systems” (Savolainen and Lahdelma, 2022). A more specific and quantifiable motive is “Zero emission building” (Andersen and Lindberg, 2021). Moving on to the optimization objectives and constraints, all of them are related to climate change. All the environmental optimization objectives identified aim to minimize greenhouse gas emissions, such as the objective to minimize the direct emissions from a biomass boiler (Behzadi and Sadrizadeh, 2023). Climate change is also the focus of environmental constraints, with “Zero emission building” being selected for one of the models found (Andersen and Lindberg, 2021). In the same way, in the articles analyzed, the environmental KPIs only quantified the global warming potential. This consistency around global warming led to a closer analysis of the indicators.

A more detailed analysis of the environmental indicators in Table 2 reveals a variation regarding the scope of the quantified impacts. For instance, Equation 1 shows an indicator used to assess the global warming potential for a district hybrid energy optimization model that only includes direct emissions from a biomass boiler, even though the model has grid electricity. Another indicator estimates the “Carbon dioxide emission reduction rate” to compare two energy models, as shown in Equation 2. It accounts for the operation emissions from the grid electricity and the heat from the district heating network. In a solar energy system study, exported energy is considered negative emissions (see equation 4). Similarly, the emissions from the grid and district heating are estimated, as shown in (Yuan et al., 2022). However, unlike the two previously shown indicators, the estimation made for the grid had a variable emissions index with monthly resolution, see equation 5. Lastly, the total yearly equivalent greenhouse gas emissions are estimated to assess the performance of an operation cost optimization model, as shown in (Berg et al., 2024). In this study, the emissions from grid-imported electricity are estimated with an hourly resolution (see equation 6). In conclusion, all the models aim to estimate the global warming potential Despite this, the scope and resolution are different.

Table 2. The mathematical definitions for environmental indicators are shown.

Reference	Indicator name	Mathematical definition	
(Behzadi and Sadrizadeh, 2023)	“CEI (CO_2 emission index)”	$CEI = \frac{CO_2\ emitted\ to\ the\ atmosphere}{\dot{E}_{Solar} + \dot{C}_{Chiller} + \dot{Q}_{Space\ heating} + \dot{Q}_{Hot\ water}}$	(eq. 1)
		CEI	Carbon Emission Index (kg/MWh)
		CO_2 emitted to the atmosphere	“Considering the carbon dioxide emitted from the biomass heater”(kg)
		$\dot{E}_{Solar}$	Electricity generated via photovoltaic thermal Panels (MWh)
		$\dot{C}_{Chiller}$	Cooling generated via absorption chiller (MWh)
		$\dot{Q}_{Space\ heating}$	Heating supplied for space heating (MWh)
		$\dot{Q}_{Hot\ water}$	Heating for domestic hot water (MWh)
(Arabkoohsar et al., 2021b)	“Carbon dioxide emission reduction Rate”	$CDERR = \frac{CDE^{SP} - CDESolar}{CDE^{SP}} \times 100$	(eq. 2)
		$CDE^{SP} = \dot{E}_{Demand} \times \lambda_{electricty} + \dot{Q}_{Demand} \times \lambda_{heat}$	(eq. 3)
		$CDE^{Solar} = \left(\dot{E}_{Bought} - \dot{E}_{Sold}\right) \times \lambda_{electricty} + \left(\dot{Q}_{Bough} - \dot{Q}_{Sold}\right) \times \lambda_{heat}$	(eq. 4)
		CDERR	Carbon dioxide emission reduction rate
		CDE^{SP}	Carbon dioxide emission Separation production (kg)
		CDE^{Solar}	Carbon dioxide emission of the solar-based systems(kg)
		$\dot{E}$	Electricity from the grid (kWh)
		$\dot{Q}$	Heat from district heating network (kWh)
		λ	Carbon dioxide emission coefficient (kg/MWh)

(Yuan et al., 2022)	"Life Cycle CO_2 emissions"	$LC_{CO2} = \sum_t E_{e,import,t} \times CO2_{El} + \sum_t E_{DH,import,t} \times CO2_{DH}$	(eq. 5)
		LC_{CO2}	Life Cycle CO_2 emissions, ($\times 10^3$ ton)
		$E_{e,import}$	Electricity imported from the grid (MWh)
		$CO2_{El}$	Monthly emission factor for electricity production (MWh)
		$E_{DH,import}$	Heat energy imported from DH (MWh)
		$CO2_{DH}$	Constant emission factor for district heating (g/kWh)
(Berg et al., 2024)	Annual "CO_2 emission equivalents"	$Tot.em_{year} = \sum_{h=1}^{8760} CO_{2eq}(h) \cdot p_t^{imp}(h)$	(eq. 6)
		$Tot.em_{year}$	Annual "CO_2 emissions from imported electricity", ($kgCO_2$)
		CO_{2eq}	Hourly "CO_2 emission equivalents" (gCO_2eq/kWh)
		p_t^{imp}	"Grid import" (kWh)

3.3. Technical strategic framework found in the analyzed studies

The technical motives and indicators found in the scientific articles can be classified into five main categories: production/demand imbalance, energy efficiency, energy storage, reliability/flexibility, and well-being. The main motive in the imbalance group is to make as much use of renewable energy onsite as possible. The equations related to the main technical indicators are shown in Table 3. The indicators related to the production/demand imbalance are self-consumption (eq. 7) and self-sufficiency (eq. 8). Moving on to the energy efficiency category, there are some specific examples (eq. 9). However, the definition from (Patterson, 1996) as the ratio of the useful output and the energy input can be used to generalize them. The concept of efficiency also applies to energy storage, equation 10 shows an indicator to evaluate a seasonal storage system performance. Furthermore, the temperature variation of thermal storage is used to assess the performance of the storage (eq. 11). Batteries are another way to store energy in the articles being analyzed. Some of its characteristics are affected by the degradation (Lin et al., 2023), which depends on the number of cycles. Therefore, the number of cycles is an indicator used when batteries are being integrated into the energy system, see equation 12. The reliability motive is related to minimizing the power interruptions (Azaza and Wallin, 2017). The indicator related to this motive is Loss of power supply probability (eq. 13). Sharing energy within a community is addressed by the indicator shown in equation 14. The last subcategory that was included within the technical framework is the well-being of building occupants shown in equations 15 and 16.

Table 3. The mathematical definitions for technical indicators are shown.

Reference	Indicator name	Mathematical definition	
(Nyholm et al., 2016)	"Self-consumption"	$\varphi_{SC} = \frac{\int_{t=t_1}^{t_2} \mathrm{M(t)dt}}{\int_{t=t_1}^{t_2} \mathrm{P(t)dt}}$	(eq. 7)
	"Self-sufficiency"	$\varphi_{SS} = \frac{\int_{t=t_1}^{t_2} \mathrm{M(t)dt}}{\int_{t=t_1}^{t_2} \mathrm{L(t)dt}}$	(eq. 8)
		M(t)	Generated electricity used inhouse in every instance (kW)
		P(t)	Instantaneous PV electricity generation (kW)
		$S(t)$	Instantaneous household electricity load (kW)
(Behzadi and Sadrizadeh, 2023)	"Energy efficiency"	$\eta = \frac{\dot{E}_{Solar} + \dot{C}_{Chiller} + \dot{Q}_{Space\ heating} + \dot{Q}_{Hot\ water}}{\dot{Q}_{Sun} + Q_{Biomass} + \dot{E}_{Chiller} + \dot{E}_{Heat\ pump} + \dot{E}_{Tank}}$	(eq. 9)
		$\dot{E}$	Electricity (MWh)
		$\dot{Q}$	Heat (MWh)

		$\dot{C}$ — Cooling (MWh) $(\dot{E}_{Solar} + \dot{C}_{Chiller} + \dot{Q}_{Space\ heating} + \dot{Q}_{Hot\ water})$ — Useful output (MWh) $(\dot{Q}_{Sun} + Q_{Biomass} + \dot{E}_{Chiller} + \dot{E}_{Heat\ pump} + \dot{E}_{Tank})$ — Energy input (MWh)
(Hirvonen et al., 2018)	"Efficiency of a seasonal energy storage system"	$\eta_{BTES} = \frac{E_{discharge}}{E_{charge}}$ (eq. 10)
		$E_{discharge}$ — Annual energy taken out of the borehole thermal energy storage (BTES) (MWh) E_{charge} — Energy injected into the storage (MWh)
(Yuan et al., 2022)	"Annual temperature variation BTES"	$\Delta T_{BTES} = T_{\text{year n+1}} - T_{\text{year n}}$ (eq. 11)
		$T_{\text{year n}}$ — Temperature of the BTES on a given year (°C) $T_{\text{year n+1}}$ — Temperature of the BTES on the immediately next year (°C)
(Meriläinen, Altti et al., 2023)	"Battery energy system (BESS) cycles"	$\mathrm{N} = \sum_{\mathrm{t=1}}^{\mathrm{T}} C_{\mathrm{t}}$ (eq. 12)
		N — Total number of cycles C_t — Number of cycles in a given time T — Time period
(Azaza and Wallin, 2017)	"Loss of power supply probability (LPSP)"	$\mathrm{LPSP} = \frac{\sum P_L - P_{PV} - P_{WT} + P_{SOC,min} + P_D}{\sum P_L}$ (eq. 13)
		P_L — Power load (kW) P_{PV} — Power from photovoltaic panels (kW) P_{WT} — Power from wind turbines (kW) $P_{SOC,min}$ — Minimum state of charge of the battery storage (kW) P_D — Power from diesel generator (kW)
(Huang et al., 2022)	"Energy Sharing Ratio (ESR)"	$r_{share} = \frac{\sum_{\mathrm{i=1}}^{8760} \mathrm{P}_i^{share}}{\sum_{\mathrm{j=1}}^{\mathrm{N}} \sum_{\mathrm{i=1}}^{8760} \max(P_{j,i}^d, P_{j,i}^s,)}$ (eq. 14)
		P_i^{share} — Power shared in the i[th] hour (kWh) $P_{j,i}^d$ — Power demand of the j[th] building in the i[th] hour (kWh) $P_{j,i}^s$ — Power supply of the j[th] building in the i[th] hour (kWh)
(Rabani et al., 2021)	"Weighted Discomfort Hours"	$\mathrm{W\_DH}_{26} = \frac{\sum_{\mathrm{k=1}}^{\mathrm{N}} A_{\mathrm{k}} \cdot DH26_k}{\sum_{\mathrm{k=1}}^{\mathrm{N}} A_{\mathrm{k}}}$ (eq. 15)
	"Weighted Predicted Percentage Dissatisfied"	$\mathrm{W\_PPD} = \frac{\sum_{\mathrm{k=1}}^{\mathrm{N}} A_{\mathrm{k}} \cdot PPDavg_k}{\sum_{\mathrm{k=1}}^{\mathrm{N}} A_{\mathrm{k}}}$ (eq. 16)
		N — Total number of zones in the building k — Index to denote a specific zone A_{k} — Area of the k[th] zone (m^2) $DH26_k$ — Discomfort hours in the k[th] zone where the indoor operative temperature exceeds 26°C during occupancy. (h) $PPDavg_k$ — Average Predicted Percentage Dissatisfied in the k[th] zone (%)

3.4. Economic strategic framework in the analyzed studies

The motives found in the literature are mainly related to cost, feasibility, volatility and some general economic concerns. Continuing with the indicators for optimization and for assessing the economic performance of the energy systems (shown in Table 4), they can be grouped depending on the analyzed life cycle stage. In some studies, like in (Rehman et al., 2018) only the investment cost was estimated, see equation 17. On the other hand, other studies analyzed the operation cost. For example, in (Salpakari and Lund, 2016) the yearly electricity cost was optimized and analyzed for a single-family building. Another example of an operational cost indicator is found in Equation 20. In this case, it is used to analyze community-level optimization. Furthermore, other studies take a more comprehensive approach from the lifecycle perspective and integrate different stages of the energy system lifespan. In (Campana et al., 2017) a scope from initial investment to salvage value is taken to analyze the lifecycle cost and levelized cost of electricity of a community energy system optimization. Another example that involves investment and operation costs can be seen in equations 23 to 26. In this study, the cumulative cash flow is used to analyze the payback performance of an energy system in a residential building.

Table 4. The mathematical definitions for economic indicators are shown.

Reference	Indicator name	Mathematical definition	
(Rehman et al., 2018)	"Overall investment cost"	$IC = C_{ST} + C_{PV} + C_{BTES} + C_{WT} + C_{HT} + C_B$	(eq. 17)
	"Building investment costs"	$C_B = C_{Wins} + C_{Rins} + C_{Fins} + C_{WIND} + C_{HR}$	(eq. 18)
		C_{ST}	Investment cost of Solar collectors
		C_{PV}	Investment cost of Photovoltaic
		C_{BTES}	Investment cost of borehole
		C_{WT}	Investment cost of warm tank
		C_{HT}	Investment cost of hot tank
		C_{Wins}	Investment cost insulation material, wall
		C_{Rins}	Investment cost insulation material, roof
		C_{Fins}	Investment cost insulation material, floor
		C_{WIND}	Investment cost of windows
		C_{HR}	Investment cost, building heat recovery
(Salpakari and Lund, 2016)	"Yearly electricity bill"	$J_{year} = \sum_{k=1}^{N} g_k(x_k + u_k + w_k)$	(eq. 19)
		N	End of optimization horizon
		g	Time-step cost
		x	State vector
		u	Control vector
		w	External data vector
(Huang et al., 2022)	"Electricity costs"	$Cost = \sum_{i=1}^{8760} P_{ex}^{cm,i} \times \tau \times X_i, \begin{cases} X_i = X_{buy}, if P_{mis}^{c,i} > 0 \\ X_i = X_{sell}, if P_{mis}^{c,i} \leq 0 \end{cases}$	(eq. 20)
		$P_{ex}^{cm,i}$	Community hourly power exchanges with the grid
		τ	Charging duration in hours
		X_{buy}	Energy injected into the storage
		X_{sell}	Feed-in-tariff
		X_i	
		$P_{mis}^{c,i}$	Aggregation of the community power mismatches

(Campana et al., 2017)	"Lifecycle Cost of the renewable based hybrid power system"	$$\mathrm{LCC}_{ren} = ICC_{ren} - \sum_{n=1}^{N} \frac{d_t}{(1+i)^n} tr + \sum_{t=1}^{N} \frac{a_t}{(1+i)^n}(1-tr) - \frac{s}{(1+i)^n}$$ (eq. 21)
		ICC_{ren} Initial capital cost of the renewables based system
		N The lifetime of the project (years) d_t Annual depreciation i Interest rate tr Tax rate a_t Annual costs s Salvage value
	Levelized cost of electricity	$$LCOE = \frac{LCC_{pv} + LCC_{bapv} + LCC_{wt} + LCC_{batt}}{EP \sum_{n=1}^{N} \frac{r_t}{(1+i)^n}}$$ (eq. 22)
		LCC_{pv} Lifecycle cost of the ground-based PV systems LCC_{bapv} Lifecycle cost of the building attached PV systems LCC_{wt} Lifecycle cost of the Wind turbine LCC_{batt} Lifecycle cost of the Battery r_t Degradation rate
(Kharseh and Wallbaum, 2019)	"Cumulative cash flow (CCF)"	$$\mathrm{CCF}_j = \frac{C_{net}}{(1+d)^j} - C_{inv}$$ (eq. 23)
	"Discount rate"	$$d = (1+g)\cdot(1+ir) - 1$$ (eq. 24)
	"Up-front cost"	$$C_{inv} = (0.340 \cdot P_{nominal} + C_{panel}) \cdot N$$ (eq. 25)
	"Net income of year ´j´"	$$C_{net,j} = (\sigma \cdot P_e \cdot E_d - P_e - P_{e,fed}) \cdot E_{fed}) \cdot (1 + er)^j - C_{O\&M,j}$$ (eq. 26)
		g Inflation rate ir Interest rate 0.340 Labor costs factor $P_{nominal}$ Nominal capacity of a PV panel C_{panel} Cost of a PV panel N Number of PV panels σ Annual saving target (%) P_e Current electricity price E_d Required annual electricity $P_{e,fed}$ Feed-in tariff E_{fed} Generated electricity that is fed into the utility grid er Annual escalation rate of electricity price $C_{O\&M,j}$ Operation and maintenance cost

4. Discussion

The quantification of the indicators in different categories across the strategic choices revealed that while most indicators in the analyzed articles focus on technical and economic aspects, environmental objectives and KPIs are considered less frequently. This presents a drawback for the environmental motives expressed in most of the articles, as they will not directly optimize and quantitatively express how much the environmental impact is reduced by the proposed optimization. On the other hand, as seen in several of the equations, the environmental and economic variables are dependent on technical performance. This means technical indicators can indirectly pass information about the performance in the other two categories. Furthermore, environmental and economic performances depend on the social and economic conditions of a location and the timeframe for the study. Therefore, if technical indicators are not used, the comparability of the different studies will be sacrificed. In consequence, multi-objective optimization can provide solutions that minimize the risk of deteriorating other variables related to the initial motives as it is also addressed in (Klemm and Wiese, 2022). They recommend multi-criteria approaches to enable more holistic optimization and planning of sustainable urban energy systems.

Another aspect of the optimization process for sustainability is the lack of a comprehensive approach in the lifecycle scope. According to (Nugent and Sovacool, 2014), there are four basic lifecycle assessment stages for PV and wind energy systems: material cultivation and fabrication, construction, operation, and decommissioning. From these stages, only the operation is considered to account for the greenhouse gas emission within the studies reviewed. This implies not considering the material extraction and manufacturing, despite having PV area or power installed as a decision variable. This could cause an underestimation of the environmental impact given that this lifecycle stage represents around 70% of the greenhouse gas emissions of a PV system (Nugent and Sovacool, 2014). This contrasts with some of the economic indicators that include the initial stage as investment costs.

A deeper analysis of the economic and technical indicators suggests that some motives shown in these two categories could not be assessed. For example, energy price volatility is mentioned in (Hajiaghapour-Moghimi et al., 2023) to set the context for an optimization study about demand response and energy storage for a PV system in Finland. However, an indicator that aims to quantify this motive is not found within this or in the other articles analyzed. Similarly, the importance of decreasing the peak power is mentioned in (Koskela, Juha et al., 2019). Despite this, there are no indicators that evaluate the intensity and/or frequency of the power peaks in the results. This situation opens the opportunity to propose indicators that cover the motives that are currently not covered by indicators for this field. Furthermore, the social strategic choices are not covered in the present review. However, the well-being indicators displayed in the results under the technical category can be viewed as a group of social indicators. Despite this, there is a significant potential for future studies around social motives and indicators.

The present review has other limitations. To start with, the analyzed indicators are limited to the subset of studies mentioned in the method. There could be additional motives and indicators in literature outside the scope of study that can be useful to fill the gaps found. Another limitation is that the motives of the optimizations are assumed to be in the introduction, stated as the societal context. It is likely that in some of the studies, the motives are more specific, such as comparing two different methods therefore they do not need comprehensive optimization. Nevertheless, the strategic framework proposed can be a useful way to define the indicators to be used in an optimization energy model.

From the previous discussion, it can be concluded that possible future research could be: (1) an analysis of the impact on environmental indicators if an optimization model only focuses on technical or economic objectives; (2) replicable indicators that quantify and help to compare the risk that economic volatility poses on energy systems investment; (3) a replicable indicator that quantifies the frequency and intensity of peaks in the power of energy systems; (4) An analysis of the consequences of considering or not material extraction and manufacturing when optimizing the design of an energy system with environmental objectives; (5) A review of indicators can be useful to match collective social sustainability motives for energy systems; (6) A review of the coherence of strategies to optimize energy systems in other regions.

5. Conclusions

The review process revealed the coherence of a group of strategic frameworks applicable to optimizing energy systems. This overview facilitates strategic decision-making, ensuring alignment between the optimization process and stakeholders' motives. Furthermore, it showed that even when environmental motives are expressed by most of the authors, a relatively low portion of the scientific articles focused on optimizing environmental objectives and quantifying environmental performance. Furthermore, the renewable energy systems' raw material extraction and manufacturing stage is not being considered in the optimization studies reviewed. This could cause an underestimation of the environmental impact of the energy system in the model, which can lead to a suboptimal design solution. These inconsistencies show the need for more comprehensive studies into the optimization of energy systems in the Nordic built environment, aiming to contribute to the solutions for environmental issues related to the solar PV energy systems in the built environment.

Another key finding is that certain objectives highlighted in the literature are not currently addressed by any existing indicators. To bridge this gap, it would be beneficial to introduce new indicators. These could monitor periods of peak energy production and demand, and measure the instability of energy prices. These indicators could provide a more comprehensive understanding of the technical risks and energy market dynamics and help stakeholders make informed decisions. They could also contribute to the development of strategies for managing the risks associated with power peaks and energy price volatility.

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