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An assessment methodology of sustainable energy transition scenarios for realizing energy neutral neighborhoods

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HIGHLIGHTS

• Scenario assessment method for realizing energy neutral neighborhoods is proposed.
• A deterministic assessment is carried out to predict future demand variations.
• Suggested LCPD based indicators provide valuable insights to decision-makers.
• Monte Carlo simulations investigate uncertainty of the decision-maker’s choice.
• A case study in the Netherlands to validate the methodology is demonstrated.

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ABSTRACT

Increasing demand for energy and emphasis on environmental sustainability has started to revolutionize the existing energy infrastructure within the built environment. In parallel, more distributed energy systems are rapidly springing up. These changes inevitably influence the design, operation and management of buildings. Recently, the energy and environmental evaluation of buildings for long-term decision-making and planning has shifted the boundaries from single buildings towards neighborhood scale. This is because buildings as a cluster can enhance the incorporation of distributed energy systems when realizing energy neutrality in the long run.

However, when assessing the energy and environmental performance of infrastructural developments at the neighborhood level, the life-cycle aspect of energy systems is rarely considered. To understand the overall impacts from production to end-of-life stage, it is essential to assess the energy and environmental performance of clean energy initiatives from a life-cycle perspective.

This paper proposes a novel decision support methodology by means of life cycle performance design-based approach to facilitate the planning process to realize energy neutral neighborhoods. The assessment methodology is developed based on scenario analysis through computational simulations. This is followed by a deterministic evaluation and the results let the decision-makers to select a suitable clean energy development scenario. The uncertainty of the selected scenario is scrutinized by performing a probabilistic sensitivity analysis using Monte Carlo simulations. A pragmatic case study has been analyzed and the results demonstrate the feasibility of exercising the proposed methodology in practice. The recommendations and limitations of realizing energy neutral neighborhoods are depicted subsequently.

1. Introduction

The concept of energy transition is gaining traction globally as various governments have set ambitious targets to move from the fossil-based energy system towards a system using a considerable amount of distributed renewable energy sources [1]. Most governments around the world such as EU-28 [2,3] and Australia [4] plan to achieve 100% renewable energy generation by the year 2050. In the EU-28 for example, the share of renewable energy in gross final energy consumption has grown rapidly from 8.5% in 2004 to almost 16.7% in 2015 [5]. Towards attaining the goals of energy transition, in addition to increase in the share of renewable energy sources, great emphasis has been placed on improving the efficiency of production systems [3] and improving energy savings [3] and flexibility [6] on the demand side.
On the production side, a visible progress and efficiency improvement can be seen in the development of combined heat and power (CHP) [7] and combined cold, heat and power (CCHP) plants [8]. These plants have efficiencies in the range of 60% with reduced carbon emissions [7]. On the demand side, a major emphasis is placed on reducing energy demand in buildings. This is because buildings account for over 30% of the world carbon emissions [9] and consume well over 30% of total primary energy [9,10]. Energy consumption in the operational phase of the existing buildings is the most accountable for environmental impacts [11,12] irrespective of the type of construction [13]. As a result, there is a major focus on individual buildings for achieving reductions in consumed energy [14]. Thus, energy neutral [15–17] and CO₂ neutral buildings [18] are being designed as options within the current energy framework. However, achieving energy neutrality is infeasible with the current set-up and composition of some of the existing buildings [19,20].

An approach being explored to tackle this encounter is by moving the boundary from a single building to the neighborhood level and upgrading the neighborhood level by making use of the local resources and infrastructure [19,21]. Effective and meaningful energy reduction gains are said to be attainable through energy sharing [22] when buildings are considered in clusters [23,24]. As a result, in recent times, there has been more emphasis on the analysis of energy saving strategies [25] and distributed energy generation at the neighborhood-level [22,26].

Aggregating buildings and introducing community renewable energy sources with storage systems may make it possible to achieve the goal of zero-energy at the neighborhood level [20]. However, the analyses of energy infrastructure developments and realization of energy neutrality at the neighborhood level is indeed still a challenge. Existing studies on neighborhood level energy framework have focused mainly on the optimal operation of renewable sources [27,28], intermittency of renewables [29], integrated decentralized energy systems [30] and integration of district heating [31–33] into neighborhoods. While some of these studies also address issues such as peak demand management with local level storage systems [22,34] and increasing energy self-sufficiency [35], they are often most focused on the operational phase of buildings. As a result, they seldom reflect the overall impacts of decentralized energy systems at the neighborhood level. Even for the decision-making aspects of clean energy initiatives, only the operational phase of buildings [36] and distributed energy sources are considered [37]. The overarching performance assessment of energy infrastructure developments including the production, operation and end-of-life stage has been evaluated by only a few researchers [31,38,39]. However, these studies then focus only on single infrastructure components (Example: PV) [39,40] or individual buildings [38].

A general conclusion drawn from these studies [38,40] is that some infrastructure components consume a reasonable amount of primary energy during its production phase. At the end-of-life, recycling of these equipment will also be cumbersome [41]. Latuusaa et al. [41] state that given the already installed PV panels and its predicted growth in Europe, by 2050, the waste PV panels quantity that should be recycled is estimated to be 9.57 million tonnes. Thus, in making long-term decisions, evaluating the energy infrastructure development initiatives over the entire lifecycle is crucial. In literature, few studies emphasized the importance of including life cycle analysis in decision-making tools [13,42]. The lack of documented literature on methodologies, tools and best practices [20] is considered a contributory factor for the deceleration in realizing energy neutral neighborhoods. There is an opportunity and also a requirement for scientific methodologies in order to deploy clean energy technologies in the most suitable manner [28].

Therefore, this study evaluates the energy infrastructure development scenarios in the life cycle perspective as a decision-support method to realize energy neutrality in the long run. This facilitates the possibility of estimating the effects of different transition scenarios and gives the opportunity to the decision maker to identify the best-value compromise or option for neighborhood-level energy infrastructure developments.

The remaining sections of this paper are divided as follows; Section 2 identifies and discusses the expected modifications with energy transition at the neighborhood level in the next 32 years (i.e. up to 2050). To develop zero-energy master planning methodologies it is important to identify and describe key indicators and drivers [20]. Therefore, Life Cycle Performance Design based indicators are introduced in Section 3 together with the overview of the assessment methodology. In Section 4, a pragmatic case study has been analyzed to validate the proposed methodology. Lastly, in Section 5, a discussion on the significance of the study is presented.

2. Influence of energy transition on building neighborhoods

At the moment, most buildings are planned to construct individually [43] despite the energy characteristics of prevailing neighborhood buildings [44]. In addition to these new buildings, a considerable amount of buildings which are present today will also exist in 2050 [21]. However, the eventual disposal of fossil-based energy systems may demand alterations in both the external and internal design and operation of these buildings [44]. For instance, currently in the Netherlands, more than 90% of the heating demand [45] is achieved by natural gas-based energy systems [46]. The alterations with energy transition are yet to be communicated to the building owners. Intriguingly, the fossil fuel demand in existing buildings can be reduced with energy refurbishment measures [35] or integrated energy branches [2]. Electrification of the heating demand of buildings [47] might be a result of integrating energy branches. The importance of integrating electricity and heating sectors [1,2] at the building level [48] is a topic that has already been addressed by different research groups [49,50]. Electrically driven heat pumps are a point of interest in such a transition. Heat pumps have been identified as a low CO₂ emission technology [51]. Thus, heat pumps could play a promising role in the level of individual buildings and neighborhoods [2,52]. In conjunction, new forms of energy carriers like hydrogen could replace gas and operated equipment inside buildings [53]. However, the willingness of the existing buildings to accommodate these changes is still debatable.

Apart from electrification of the heating division with the individual approach using heat-pumps, a number of area-specific collective measures also have been introduced in the literature with decentralized district heating, cooling networks [54] and 4th generation low-temperature heating grids at the neighborhood level [55] in order to satisfy the thermal energy demand. Moreover, buildings itself are a viable option for providing flexibility [6] to the demand side with the use of energy storage systems [56,57]. Buildings can contribute to the needed energy flexibility [58] through energy sharing and exchange [59] among themselves within a neighborhood. These techniques will claim additional platforms allowing interchange of energy options [44].

In addition, a building neighborhood can be compact [60] as of an urban condition or sprawling (rural) [61]. Likewise, a neighborhood can range from a cluster of buildings to the city level. The pace of transition and the necessary infrastructure developments vary depending on factors such as focused neighborhood status, population, geographical location and available resources. Since the term ‘neighborhood’ is unique in character [62], a clear boundary and a description are essential when studying a neighborhood.

3. Proposed methodology with performance indicators

The above-discussed factors lead to the questions; how to evaluate the sustainable performance of building neighborhoods with different infrastructure transition scenarios and what methods can be used to quantify the key drivers in the life cycle perspective. This evaluation is challenging because of the several uncertain variables [27], the role of
stakeholders (decision makers) [36] and the long lifespan of buildings [13] and infrastructural energy systems [42]. Thus, the decision support methodological framework in the life-cycle perspective should also factor in future uncertainties. Life Cycle Performance Design (LCPD) [42] and Key Performance Indicators (KPIs) [63] are techniques which are capable of such applications.

3.1. LCPD

LCPD is a commonly used method for evaluating the performance of an asset over its entire lifetime [13]. LCPD has been used in building construction industries over a long period to analyze the performance of building materials [64]. Recently, infrastructure industries use this method to analyze the performance of energy services (electricity, gas etc.) over the life cycle of infrastructure apparatuses [64]. Even though there is no definite classification, LCPD studies can be categorized into two major streams namely, Life Cycle Performance (LCP) and Life Cycle Costing (LCC) [65]. LCP can be further divided into Life Cycle Energy Analysis (LCEA) and Life Cycle Carbon Emission Assessment (LCCO2A) [13]. On a border perspective, LCP is the evaluation of total environmental impacts associated with products and services during the life-span [65]. Over the life cycle, evaluating the energy consumption as a resource input and evaluating the CO2 emissions as an output is represented by LCEA and LCCO2A respectively [13]. Fig. 1 illustrates the classification of LCPD exercised in this paper. The LCPD associated with energy infrastructure (specifically electricity, gas and thermal energy) at building and neighborhood levels is the emphasis of this research. Studies that have used the LCPD approach in energy infrastructure development are presented in Table 1.

Relatively a very few number of scientific papers can be found on neighborhood level system-wide energy demand and environmental performance analysis in the life cycle perspective [31] and they are mostly heterogeneous [66]. Lotteau et al. [66] have addressed the LCE and CO2 emissions at 21 different neighborhoods summarizing 14 related research papers. Anyhow, scenario analysis with energy transition is not studied in these papers.

3.2. KPI

Quantifiable measures used to evaluate the key performance of a product or process are KPIs [26,27]. The literature states, KPIs have been used on different occasions in order to identify potential improvements associated with buildings [69] and energy infrastructure [63]. While some researchers imply close monitoring of achievements by KPIs is needed to identify the potential of distributed energy systems [63], others emphasize the importance of including KPIs in planning tools [70]. Identifying different stakeholder characteristics [71] and analyzing neighborhood energy performance with improved local energy infrastructure is a possibility with KPIs [23].

3.3. LCPD based KPIs

A combined approach of LCPD and KPIs provide a constructive methodology to evaluate the level of sustainability and reflect the lifetime performance of both buildings and energy infrastructure. This is hereby named as LCPD based KPIs. Identifying the development roadmap is the main objective of performing such a practice in order to reach short-term (2020) and long-term (2030–2050) goals. Studying the mentioned research papers (Section 3.1 and 3.2) lead to the realization of LCPD based KPIs (Fig. 2) for the analysis of buildings and local energy infrastructure under two main scopes: economic and environmental.

| Reference        | Scale       | Energy infrastructure | Performance analysis |
|------------------|-------------|-----------------------|----------------------|
|                  | Building    | Neighborhood          | Cost | Energy | CO2 |
| Chau et al. [13] | ✓           | ✓                     | ✓    | ✓      | ✓   |
| Bartolozzi et al. [31] | ✓           | ✓                     | ✓    | ✓      | ✓   |
| Beccali et al. [38] | ✓           | ✓                     | ✓    | ✓      | ✓   |
| Ristimaki et al. [65] | ✓           | ✓                     | ✓    | ✓      | ✓   |
| Lotteau et al. [66] | ✓           | ✓                     | ✓    | ✓      | ✓   |
| Sosa et al. [67] | ✓           | ✓                     | ✓    | ✓      | ✓   |
| Almeida et al. [68] | ✓           | ✓                     | ✓    | ✓      | ✓   |

Fig. 1. Classification of LCPD exercised in this research paper.

Fig. 2. Categories and subcategories of LCPD based KPIs on assessing the neighborhood level energy systems with buildings.

Table 1
Outline of the articles on LCPD.
environmental. The combination of economic and environmental dimensions claimed to complement each other in the long run. The most viable options can be obtained by the intersection of economic feasibility and environmental impacts. Examples of LCPD based KPIs to assess the energy systems at building and neighborhood levels are presented in Fig. 3.

The indicators presented under ‘Buildings’ category can be used to assess the active energy conservation techniques (dynamic blinds, lighting control, etc.) associated with buildings and energy systems inside the buildings (boilers, chillers, etc.). The indicators used to monitor the area specific infrastructure modifications categorize under ‘Local energy systems’. For example, PV installation, collective heat pump systems and energy storage systems categorize under local energy systems within a neighborhood. For the analysis of the interaction between buildings and infrastructure, additional ‘Other’ indicators are introduced. These indices additionally count the uncertainties and future changes that could occur in equipment costs, energy tariffs, demands, population in the particular neighborhood etc.

3.4. Overview of the methodology

The proposed methodology illustrated in Fig. 4 consists of four steps and described below in detail.

The methodology is focused on the existing building stock and it can be used to analyze any type of building or any number of buildings ranging from a very few buildings to a larger scale.

- **Step 1: Identification**: In the decision-making process, the first step is to define the neighborhood boundary with the included number of buildings. This selection is dependent on the stakeholder (decision-
makers) inputs and interest and willingness of the building owners to participate. Then, according to the geographical area, distinguished area-specific measures, local knowledge and available resources, the realizable scenarios can be identified intrinsic to the neighborhood. In this context, scenarios define the different clean energy initiative options. Examples of different scenarios:

(a) S1 = Individual heat pumps for each building with solar PV on rooftops of all the buildings in the neighborhood
(b) S2 = Collective heat pump system for all the buildings in the neighborhood with a separate thermal grid and solar PV on rooftops of all the buildings

The overview of the neighborhood boundary selection is illustrated in Fig. 5. The buildings in the neighborhood are numbered Bi where 1 < i < n. For example, buildings in neighborhood 1 could be privately owned by one company. Therefore, they can establish their own energy neutrality scenarios with only these buildings.

- **Step 2-Computational analysis and calculations**: In this step, the energy performance of the identified scenarios are estimated using simulation models.

Prior to estimating energy performance of scenarios, it is imperative to know the current energy consumption and demand profiles of the buildings. In general, two different modeling approaches are used to estimate the demand profiles of the buildings namely classical modeling and data-driven modeling [72]. Classical modeling typically develops around the physics of the system. Building simulation programs such as EnergyPLUS, TRNSYS can be used and it requires a large number of building parameters. On the other hand, data-driven modeling is easier and typically start from measurement data collected from the building energy management systems. If sufficient data are available, this could be considered more reliable than the classical modeling [72]. Both of these modeling approaches can be applied in the computational analysis to estimate the current demand profiles of the buildings.

Subsequently, the annual energy performance of candidate scenarios is estimated with an appropriate simulation tool (MATLAB, PVSyst, EnergyPlus etc.) [34,73] using the above-obtained energy demand profiles of the buildings. For PV, energy storage and heat pump related computational analysis, it is important to have smaller data resolutions such as hourly energy consumption to identify the accurate energy performance. The derived energy performances of different scenarios (S1, S2, ..., Sm) are illustrated as in Fig. 6 according to different energy carriers (EC1 = Grid Electricity, EC2 = Grid Gas, EC3 = Hydrogen, ..., ECn).

Note: In Fig. 6, Scenario 1 represents the operational phase energy consumption of the current situation and Scenario 2 to Scenario m represent the new operational phase energy consumption of the buildings with the introduced clean energy initiatives.

For example:

(a) Scenario 1 = Individual boilers and compression chillers in each building
(b) Scenario 2 = Hybrid system with individual heat pumps and boilers for each building
(c) Scenario m = Collective heat pumps system for all the buildings in the neighborhood with sensible thermal storage and solar PV on rooftops of the buildings

- **Step 3-Performance assessment using KPIs**: This step introduces Lifecycle performance design based KPIs so that the decision-making process encompasses life-cycle perspective of the energy infrastructure development scenarios. The energy consumption, CO2 emissions and associated costs of energy infrastructural components during the pre-utilization stage (production of equipment), operational stage (energy consumption of the buildings and maintenance of equipment) and end-of-life stage (recycling or demolishing of equipment) is included in this analysis. Here, equipment exemplify boilers, chillers, PV panels, gas pipes, heat pumps etc. The performance is continuously evaluated until 2050.

In order to predict the operational stage energy demand variation of the buildings until 2050, knowledge-based deterministic approach [27] is used. The term ‘knowledge-based’ denote the probabilities obtained with an accumulation of available facts and information. The deterministic approach precisely projects the demand variations of the candidate scenarios through knowledge-based probabilities. The final resulting performances of the scenarios can be represented by a performance matrix as demonstrated in Table 2 for the easy understanding of the decision makers.

Applying the knowledge-based approach in this step allows the formation of neighborhood plans without going through time consuming processes and computational efforts. Otherwise, if all combinations of uncertainties are applied to the scenarios in this step, it may result in very high computational time and costs.

### Table 2

| Scenario | Performance category |
|----------|----------------------|
|          | Life cycle energy    | Life cycle CO2 | Life cycle costs |
| S1       | LCE1                 | LC(O2)1        | LCC1            |
| S2       | LCE2                 | LC(O2)2        | LCC2            |
| ...      | ...                  | ...            | ...             |
| Sm       | LCEm                 | LC(O2)m        | LCCm            |
Table 3
Opportunity loss matrix.

| Scenario | Performance category | Life cycle energy | Life cycle CO₂ | Life cycle costs |
|----------|----------------------|------------------|----------------|----------------|
| S₁       | LCE₁ - B₁            | LCC₁ - B₁        | LCC₁ - B₁      |
| S₂       | LCE₂ - B₁            | LCC₂ - B₂        | LCC₂ - B₂      |
| ...      | ...                  | ...              | ...            |
| Sₙ       | LCEₙ - B₁            | LCCₙ - B₂        | LCCₙ - B₂      |

- **Step 4-Decision making:** In order to choose a development scenario from among the set of other possibilities, the performance matrix is converted to the opportunity-loss (regret) matrix. Using the minimal performance in each category of the performance matrix, the regret matrix is obtained by applying the minimax regret method [36]. By communicating the performance matrix with the opportunity loss matrix (Table 3), the decision maker is allowed to select a suitable development scenario.

\[
\text{Opportunity loss} = |\text{Best value} - \text{Actual value}|
\]

Best value (Bᵢ) = Minimum value of each performance category

Example: B₁ = min (LCE₁, LCE₂, ..., LCEₙ)

In this manner, when all the scenarios are analyzed without giving a preference, the decision-maker is well-informed about what other scenarios are capable of and what the opportunity losses are. Most of the decision-making procedures found in the literature start with the development scenario. The role of the decision-maker (building owners, consultants, policymakers) in compromising options could be exterminated. The robustness of the decision-maker selected scenario is identified by performing a probabilistic sensitivity analysis. This implies the assignment of uncertainties to the knowledge-based probabilities. KPIs such as energy carrier prices, primary energy factors, energy demand variation, etc. are uncertain parameters and this step entails allocating a mathematical explanation to the uncertainty and capturing the stochastic nature of the performance parameters (Fig. 7).

In literature, Monte Carlo simulation is considered a best-practice to assign probabilistic descriptions [74,76]. Monte Carlo analysis samples uncertain parameters based on a probabilistic distribution [76]. For each of the j uncertain KPI, this describes the generation of N random samples within their assumed probability distributions. Matrix Xⱼ represents all the samples generated for a particular uncertain parameter. In which, Yᵢ,k represent the value of parameter yᵢ (1 ≤ i ≤ N) in the year k (2018 < k < 2050).

\[
\text{Matrix} Yⱼ = \begin{bmatrix}
Y_{1,2018} & \ldots & Y_{1,2050} \\
\vdots & \ddots & \vdots \\
Y_{N,2018} & \ldots & Y_{N,2050}
\end{bmatrix}
\] (1)

After the generation of the sample matrix, the N number of Monte Carlo evaluations are obtained in Matrix Xⱼ for the uncertain parameter j. Fig. 8 illustrates the deviation of the results calculated in step 3. The most influential uncertain parameters can be observed from Fig. 8.

\[
\text{Matrix} Xⱼ = \begin{bmatrix}
\bar{Y}_{1,2018},\bar{Y}_{1,2019},...,\bar{Y}_{1,2050} \\
\vdots \\
\bar{Y}_{N,2018},\bar{Y}_{N,2019},...,\bar{Y}_{N,2050}
\end{bmatrix}
\] (2)

Finally, the threats, risks and barriers to realizing the scenario are analyzed using a multi-criteria decision-making matrix (Table 4) [77]. Each threat/risk or bottleneck is given a weight and compared in the matrix as shown in Table 4 below. On the weight scale, 1 represents the least threat/risk while 10 represents the highest.

This creative methodology brings forth the life cycle perspective of energy infrastructure development scenarios while effectively helping all the involved parties to understand the consequences of different scenarios before making decisions.

4. Case study

A case study has been evaluated and discussed below using different scenarios and suggested performance indicators. This example is shown to validate and discourse only the life cycle energy-based performance indicators discussed in Section 3 and highlighted in Fig. 9.

In the case study, the following KPIs (Table 5) have been used per scenario evaluated. No changes in the buildings’ gross surface area and no functional changes of the buildings are assumed throughout the evaluation.

4.1. Case study: Princenhage

As the case study for this paper, a neighborhood located in the Netherlands named ‘Princenhage’ is investigated. The location of the selected neighborhood and the buildings are presented in Fig. 10. This is an already established neighborhood with a combination of commercial and residential buildings.
4.2. Scenario identification

Till date, the largest portion of the energy used in Princenhage is derived from fossil sources. Nevertheless, after performing a location analysis, it was identified that the district has a considerable possibility to utilize renewable energy sources such as solar and earth (geo) energy. The potential of the PV-panels is based on an average yield of 123 kWh/m² per year. In this study, one probable scenario has been envisioned that generates, stores and distributes energy to the buildings. This scenario is compared with the business as usual (BAU) case. The scenario is scrutinized with the installation of solar panels and applying a centralized ground source heat pump system for heating and cooling applications. Such a system, when linked with energy storage, enables improved consumption of locally produced energy and gas-free energy transition.

4.3. Computational analysis and calculations

The neighborhood presented in Fig. 9 is composed of a commercial building and eighteen residential buildings. The commercial building’s

| Table 4 | Multi-criteria matrix. |
|---------------------------------|-------------------------|
| Criteria (Threats/ Bottlenecks/Risks) | Weight |
|---------------------------------|---------|
| Threat of operational feasibility of the technologies used in the scenario |  | |
| Technical maturity of energy technologies |  | |
| System reliability |  | |
| Resource feasibility |  | |
| Acceptance of people |  | |
| Institutional barriers |  | |
| Technical barriers |  | |
| Finance barrier |  | |
| Political and regulatory barrier |  | |
| Energy market barrier |  | |
| Environmental barriers |  | |

...
load data was acquired from the building energy management system (BEMS) and the energy demand data of dwellings were acquired from Nederlandse Energie Data Uitwisseling (NEDU) [78] and Gemiddeld energieverbruik – MilieuCentraal [79]. The different characteristics of the buildings obtained are presented in Table 6.

### 4.3.1. Scenario 1: Business as usual (BAU) case

Scenario 1 is the reference BAU case with conventional heating and cooling energy systems already installed in the buildings described in Table 6. The cooling demand is delivered by electricity using compression chillers and heating demand is fulfilled by natural gas boilers. The collective demand variation of all the buildings in the neighborhood is illustrated in Fig. 11. The electricity demand in Fig. 11 represents the electricity consumed for appliances and hot water without including the electricity needed for cooling. It is assumed that the hot water demand is satisfied with electric boilers. Cooling demand is drawn to the minus scale for the clear visualization. An average day consists of 24 h is presented in this figure for each season.

### 4.3.2. Scenario 2: an envisioned scenario with heat pump, thermal storage and PV

This scenario is studied with the installation of solar panels on the rooftop of the commercial building described in Table 6. Combining the commercial building with houses (Table 6) has an advantage over maximizing the consumption of locally produced energy because of the different demand profiles. A local distribution grid assists in delivering the locally produced energy among the buildings. For heating and cooling purposes a centralized ground source heat pump scheme with sensible water-based thermal storage is exploited. The heat pumps and thermal storage system are optimally used in a way that the total heating demand could be provided by this arrangement via a communal distribution network. During the spring, autumn and summer, the heat pumps which does not deliver heating are reversed operated to provide cooling. Chillers are responsible for delivering the excess cooling demand during spring, autumn and summer seasons. The scenario is illustrated in Fig. 12. The symbols $Q_{net, heating}$ and $Q_{net, cooling}$ represent the collective heating demand and cooling demand of the cluster of buildings. Electricity need for appliances and hot water is symbolized by $P_{net, electricity}$.

The computational analysis of the envisioned scenario is performed using the energy hub approach [80,81] based on a mixed integer linear programming (MILP) model [27,28]. This modeling approach is capable of identifying the optimal dispatch of distributed energy sources.

### Table 6

Characteristics of the buildings.

| Building               | Constructed year (renovated year) | Gross surface area (m²) | Energy demand (MWh/year) |
|------------------------|-----------------------------------|-------------------------|--------------------------|
| Building 1 (Office)    | 1993 (2013)                       | 1540                    | 69                       | 50                       |
| House 1 (Detached)     | 1991 (2012)                       | 125                     | 14                       | 3.6                      |
| House 2 (Detached)     | 1955 (2012)                       | 69                      | 8                        | 3                        |
| House 3 (Detached)     | 1959 (2012)                       | 70                      | 8                        | 3                        |
| House 4 (Detached)     | 1964 (2012)                       | 91                      | 10                       | 3                        |
| House 5 (Detached)     | 1964 (2012)                       | 171                     | 18                       | 4.2                      |
| House 6 (Detached)     | 1963 (2012)                       | 142                     | 16                       | 3.6                      |
| House 7 (Terraced-corner) | 1975 (2012)                  | 103                     | 10                       | 3.6                      |
| House 8 (Terraced)     | 1975 (2012)                       | 103                     | 8                        | 3.6                      |
| House 9 (Terraced)     | 1975 (2012)                       | 103                     | 8                        | 3.6                      |
| House 10 (Terraced-corner) | 1975 (2012)                   | 103                     | 10                       | 3.6                      |
| House 11 (Terraced-corner) | 1975 (2012)                  | 103                     | 8                        | 3.6                      |
| House 12 (Terraced)    | 1975 (2012)                       | 103                     | 8                        | 3.6                      |
| House 13 (Terraced)    | 1975 (2012)                       | 103                     | 8                        | 3.6                      |
| House 14 (Terraced)    | 1975 (2012)                       | 103                     | 8                        | 3.6                      |
| House 15 (Terraced)    | 1975 (2012)                       | 103                     | 8                        | 3.6                      |
| House 16 (Terraced)    | 1975 (2012)                       | 103                     | 8                        | 3.6                      |
| House 17 (Terraced)    | 1975 (2012)                       | 103                     | 8                        | 3.6                      |
| House 18 (Terraced-corner) | 1975 (2012)                  | 103                     | 10                       | 3.6                      |
| Total                  | 3442                              | 247                     | 113.6                    |
and optimal capacity of the thermal storage system and heat pumps system [27]. The simulations were programmed using MATLAB software. The relevant objective function, energy balance equations and system constraints used in the simulation are presented in Eqs. (3)–(5).

Objective function: The equivalent annual cost \( C_{\text{Total}} \) of the system calculated for a typical year with a set of average days for each season consisting of 24 h is used as the objective function. The equivalent annual cost is the sum of annualized investment cost \( C_{\text{Investment}} \) of all clean energy initiatives (installation of PV \( C_{\text{PV}} \), thermal storage \( C_{\text{ThermalStorage}} \) and heat pump \( C_{\text{HeatPump}} \)) and total operational costs \( C_{\text{Operation}} \) of each energy carrier. \( C_{\text{EnergyCarrier}} \) symbolizes the energy consumption and \( C_{\text{EnergyCarrier,t}} \) represent the tariff per energy carrier. The objective function is nested within technology (design parameters) and system related constraints.

\[
C_{\text{Investment}} = C_{\text{HeatPump}} + C_{\text{PV}} + C_{\text{ThermalStorage}}
\]

\[
C_{\text{Operation}} = \sum_{i=1}^{H} I_{\text{EnergyCarrier}} * C_{\text{EnergyCarrier,t}}
\]

\[
\min C_{\text{Total}} = C_{\text{Investment}} + \sum_{i=1}^{T} C_{\text{Operation}(t)}
\] (3)

Constraints: The feasible region of each decision variable are presented under constraints. The technology parameters such as charge/discharge possibility of storage systems \( Q_{\text{Charge}}, Q_{\text{Discharge}} \), minimum capacities \( Q_{\text{HP,min}}, Q_{\text{TS,min}}, P_{\text{PV,min}}, Q_{\text{Chiller,min}} \) and maximum capacities \( Q_{\text{HP,max}}, Q_{\text{TS,max}}, P_{\text{PV,max}}, Q_{\text{Chiller,max}} \) of the energy systems are implemented under the constraints.

\[
Q_{\text{out,heating}}(t) = Q_{\text{HP,heating}}(t) + Q_{\text{TS,in}}(t) - Q_{\text{TS,out}}(t)
\]

\[
Q_{\text{out,cooling}}(t) = Q_{\text{HP,cooling}}(t) + Q_{\text{Chiller}}(t)
\]

\[
P_{\text{net,electricity}}(t) = P_{\text{grid}}(t) - P_{\text{HP,heating}}(t) - P_{\text{HP,cooling}}(t) - P_{\text{Chiller}}(t) - P_{\text{PV,grid}}(t)
\] (4)

\[
P_{\text{grid}} \geq 0
\]

\[
Q_{\text{Chiller,min}} \leq Q_{\text{Chiller}}(t) \leq Q_{\text{Chiller,max}}
\]

\[
Q_{\text{HP,min}} \leq Q_{\text{HP,heating}}(t) \leq Q_{\text{HP,max}}
\]

\[
Q_{\text{TS,min}} \leq Q_{\text{TS}}(t) \leq Q_{\text{TS,max}}
\]

\[
P_{\text{PV,min}} \leq P_{\text{PV}}(t) \leq P_{\text{PV,max}}
\]

\[
Q_{\text{Charger}}(t) \leq Q_{\text{HP,heating}}(t) - Q_{\text{HeatingLoad}}(t)
\]

\[
Q_{\text{Discharge}}(t) \leq Q_{\text{HeatingLoad}}(t) - Q_{\text{HP,heating}}(t)
\] (5)

The resulted supply and demand variations are depicted in Fig. 13 and Fig. 14. In Fig. 13, the symbols TS-In and TS-out represent the thermal storage charging and discharging during an average day in each season. In Fig. 14, the total electricity demand represents the electricity needed for heat pumps operation, chillers operation, hot water (electric boiler) and appliances. If there is an additional production from PV, it is assumed that the excess is sent back to the grid.

A 100% gas-free energy system with an energy self-sufficiency (autonomy) of 32% is achievable with this scenario through 45 kW heat pumps system, 70 kWh sensible water-based thermal storage, 28 kWp of PV panels installed over the flat rooftop of the commercial building. The energy autonomy can be further increased by installing PV panels on the rooftops of the houses. However, this simulation results only discuss the PV panels installed on the rooftop of the commercial building. The resulted annual energy consumption of the scenarios per energy carrier is illustrated in Fig. 15.

4.4. Performance assessment using KPIs

This step calculates the energy performances of the above scenarios in the coming years using the deterministic approach. The KPIs which indicate the future variations and the carefully chosen knowledge-based probabilities are presented in Table 7. The 1% decline in heating demand is due to the use of efficient equipment and technologies and the decreasing heating degree days throughout Europe [82]. The value 1% is chosen according to the statistics presented by CE-Delft [46].
2020, the gas demand is assumed to be constant. From the statistics revealed by Energy Research Center of the Netherlands (ECN), the gross final electricity demand rises approximately by 1% each year in the Netherlands [83]. This same percentage is used as the primary electricity demand increment of the neighborhood. No functional changes or building surface area changes are assumed throughout the calculation. With these knowledge-based probabilities, the estimated energy demand values of scenario 1 and 2 for the years 2020, 2030 and 2050 are presented in Fig. 16. For PV produced electricity a module degradation of 0.59% (Table 8) is used in the calculation.

### 4.5. Life cycle energy performance

After estimating the primary energy demand from 2018 to 2050 using knowledge-based probabilities (Sections 4.3 and 4.4), life cycle energy performance of the two scenarios is calculated using necessary KPIs. Fig. 17 and the Sections 4.5.2, 4.5.3 and 4.5.4 describe the system boundaries and the relevant interpretations respectively. In the life

---

**Table 7**

| KPI                          | Knowledge-based probabilities |
|------------------------------|------------------------------|
| Heating energy demand deviation | 1% reduction from 2020 onwards until 2050 |
| Electricity demand deviation  | 1% increment each year until 2050 |

---

**Fig. 13.** Heating using heat pumps and thermal storage.

**Fig. 14.** PV production and electricity consumption from the grid.

**Fig. 15.** Annual energy consumption of the scenarios.
cycle calculation, fuel energy for transportation of equipment from industrial site to the required location is not considered owing to the ambiguity. Installation and minor annual maintenance are not counted due to lack of data availability. On the other hand, the contribution of these components towards life cycle energy consumption is negligible [38,84]. The applied specifications of gas boilers, chillers, PV systems and heat pumps can be found in Table 8. The data have been sourced from Ecoinvent [85] and relevant research papers presented in Table 8.

Finally, the total life cycle energy performance is calculated using equation (6) from the year 2018 to 2050 including primary energy factors (4.5.1).

Fig. 16. Estimated energy demand values with knowledge-based analysis, comparison BAU (Left) and scenario 2 (Right).

Fig. 17. Considered energy consumption during the lifetime of boilers, chillers, PV panels and heat pumps.

Table 8
Characteristics and cradle to gate energy of the components.

| Equipment                  | Characteristics | Lifetime (Years) | Primary energy (MJ) | Reference |
|----------------------------|-----------------|------------------|---------------------|-----------|
| Solar PV                   |                 |                  |                     |           |
| - Peak power               | 190 Wp          | 30               | 1 m² of module PV   | [84]      |
| - Performance ratio        | 0.8             |                  | Inverter            | [91]      |
| - Module degradation       | 0.59%           |                  | BOS                 | [40]      |
| - EPBT                     | 6.26 years      |                  |                     | [39]      |
| Inverter                   |                 |                  |                     |           |
| - EPBT                     | 0.97 years      |                  |                     |           |
| BOS (Mounting structure/Cables) | 40           |                  |                     |           |
| - EPBT                     | 0.87 years      |                  |                     |           |
| Battery storage            |                 |                  |                     |           |
| - Type                     | Li-Ion          | 20               | Per kg Fossil fuel  | [92,93]  |
| - Efficiency               | 90%             |                  | Electricity         | 32.4      |
| - Energy density           | 150 Wh/kg       |                  |                     |           |
| - Life cycles              | 5000            |                  |                     |           |
| Compression chiller        |                 | 15               | 1 chiller Electricity 539.14 | [38] |
| - EER                      | 2.5             |                  | Fossil fuel         | 786.58    |
| - Cool Capacity            | 14 kW           |                  |                     |           |
| Boiler (Condensing)        |                 | 20               | 1 boiler Electricity 79.92 | [38] |
| - Efficiency               | 90%             |                  | Fossil fuel         | 116.6     |
| - Heat Capacity            | 24 kW           |                  |                     | [90]      |
| Pipe insulation            |                 | 50               | 1 m² of material    | 52.98     |
| - Material                 | Glass wool      |                  |                     |           |
| Piping                     |                 | 40               | 1 m of pipe length  | 175       |
| - Material                 | Steel           |                  |                     |           |
| Heat pump (Water source)   |                 | 30               | 1 Heat Pump Electricity 337 | [96] |
| - Capacity                 | 10 kW           |                  | Fossil fuel         | 875       |
| - COP                      | 4               |                  |                     |           |
| - EER                      | 3               |                  |                     |           |
The primary energy factor (PEF) is a numerical coefficient which describes the amount of primary energy used to generate a unit of electricity or a unit of usable thermal energy. It is a derivation from national or annual average [86] of renewable and non-renewable energy generation mix. The Energy Performance of Building Directive (EPBD) 2010, indicates that the energy performance of buildings should be conveyed by primary energy index kWh/m² per year [87] based on PEF per energy carrier. In this calculation, the current Netherlands’ reference value of electricity PEF 2.56 [88] is used for the year 2018. Due to the ever-increasing renewable energy share in the energy mix, after the year 2018, this value is taken to be decreasing to reach a factor of 2 by 2050. This decrement is assumed because current European average PEF is 2.5 and the expected value in the future is 2.0 [86]. In place of on-site PV produced electricity, PEF is taken as 1.0 [89] and for natural gas, it is assumed to be 1.1 [86].

### 4.5.2. Pre-utilization stage energy use (Cradle to gate)

Cradle to gate system boundary is applied for the calculations of pre-utilization stage energy consumption. The manufacture and assembly primary energy consumption [90] of each equipment described in Table 8 are used for the calculations. At the end of the lifetime, the equipment are assumed to be replaced.

### 4.5.3. Operational stage energy use

The operational stage primary energy consumption of natural gas and electricity from the year 2018 to 2050 is illustrated in Fig. 18. In these graphs, the PEFs described in Section 4.5.1 is taken into account and the energy consumption is presented in kWh/m²/year. The PEFs used in the calculation are presented in Table 9.

### 4.5.4. End-of-life stage energy use

At the end-of-life, the equipment are either demolished or recycled. End-of-life energy consumption was calculated according to the numerical values found in different research papers. For boilers and chillers, the values appeared in [38] are considered while for PV panels, findings of [41] are used.

### 4.6. Life cycle energy performance of scenarios

Using Eq. (6), the cumulative life cycle energy performance is calculated for the two scenarios and compared with percentages in Table 10. For each scenario, the pre-utilization, operation and end-of-life stage energy use are given as a percentage of the total energy consumption. Note that only the LCEP related to energy infrastructure and energy consumption of buildings are presented in these calculations.

The operational stage marks the largest contribution in both scenarios. It is worthwhile noticing in scenario 2, about 2.5% of the primary energy is consumed at the pre-utilization and end-of-life stages of the infrastructural components. Distributed energy sources are attractive when it comes to the reduced operational stage primary energy consumption of the buildings. However, these equipment utilize a reasonable amount of energy in the manufacturing and recycling process. The energy consumption of these stages will become further visible with the different measures taken to reduce the operational stage energy consumption [31].

### 4.7. Decision making

For a better understanding of the decision maker, the performance matrix (Table 10) is translated to the opportunity-loss matrix. Table 11 demonstrates the opportunity-loss considering life cycle energy performance of the analyzed two scenarios. The best performance in terms of life cycle energy is given by scenario 2. Therefore, if scenario 1 is selected by the decision maker, an opportunity loss is identified.

If the decision maker has selected scenario 2, the next step is to

---

**Table 9**

| PEF                | 2018  | 2020  | 2030  | 2050  |
|--------------------|-------|-------|-------|-------|
| Grid electricity   | 2.560 | 2.525 | 2.350 | 2.000 |
| Grid gas          | 1.100 | 1.100 | 1.100 | 1.100 |
| Renewable electricity | 1.000 | 1.000 | 1.000 | 1.000 |

---

**Table 10**

Total life cycle energy performance from 2018 to 2050.

| Scenario | 1     | 2     |
|----------|-------|-------|
| Total (GJ/m²) | 18.6  | 13.3  |

---

* m² presents the total gross floor area of the buildings.
The deviation of the results due to variable parameters. A Monte Carlo analysis is completed using two variable KPIs namely, primary energy factor for grid-electricity and cooling demand. Table 12 presents the description of the variables and Fig. 19 shows the life cycle energy consumption deviation due to these uncertainties. The deviation range of PEF is taken as 2.56 to 1 because 2.56 is the current value for grid electricity and 1 is the minimum it can reach. In place of the cooling demand, 0% to 5% increment of cooling demand each year is assumed. This is due to the increasing number of cooling degree days in Europe [82]. For each of these uncertain distributions, 10,000 variations have been calculated in order to obtain Fig. 19. Operational stage energy consumption is the largest contributor to these deviations of the results. It is safe to mention that PEF has a reasonable influence on the life cycle energy performance of this scenario. PEF becomes lower when the connected renewable energy sources to the electricity grid are higher. Therefore while improving the demand side, the efficiency improvement and integration of renewable energy sources to the production side of the electricity grid is also equally important as discussed in Section 1.

5. Discussion and future work

An original assessment methodology for realizing energy neutral neighborhoods with scenario analysis is purposed in this study using a life cycle perspective. The methodology presents a four-step framework. The first step identifies area specific scenarios with a location analysis and stakeholder inputs. The second step comprises of the computational simulation where the annual energy performance of the scenarios are calculated. The knowledge-based deterministic analysis estimates the future operational stage energy demands of the buildings (up to 2050) in the third step. In order to avoid different types of trade-offs, comparing the scenarios in a life-cycle viewpoint is important. Therefore, the production and end-of-life stage energy and environmental impacts of the infrastructure development scenarios are included in the calculation. This helps the decision-maker to prioritize the preference according to LCC, LCE or LCCO2 performance. Given the uncertain nature of some performance indicators, knowledge-based practice is insufficient. Therefore, the fourth step pertains to uncertainty assessment of the decision maker’s preference scenario. It inspects the deviation of the knowledge-based analysis results using Monte Carlo simulations. The four-step methodology is demonstrated using a case study with the LCE performance related KPIs.

The proposed methodology can be considered more than merely providential since energy neutrality is an objective of the European building directives. It is easily used by decision makers to identify the robustness of the energy infrastructure developments at the neighborhood level. When the pre-utilization and end-of-life stage of the energy infrastructural equipment are introduced in the decision-making methodology, it provides sufficient awareness to the decision-maker of how much energy, CO2 emissions and costs are actually involved in the total transition process. This is rarely found in the currently available decision-making methodologies. Additionally, the uncertainty assessment contributes to attaining robust energy systems in practice.

When identifying different scenarios according to geographical location, this study has acknowledged research gaps that can be exploited with future integrated energy systems at the neighborhood level. A considerable amount of research can be found for electricity grid evolution (Example: Smart grids) and a moderate amount of research can be found for the heating-cooling grid evolution (Example: 4th generation grids). Even though this is the case for electricity grid and heating-cooling grid separately, the integration of different demand sectors (Example: using heat pumps for converting electricity to heating-all electric) at the neighborhood level is less explored. Moreover, energy sharing/exchange between buildings with local level energy storage systems and impacts of phasing out fossil fuels are unavoidable matters that should be studied. This transition is taking place at a moment when a considerable proportion of the installed central generation plants, transmission and distribution network assets (Example: gas pipes) reach the end of their usable lifetime. This could be seen as a great opportunity to modernize the decentralized supply systems, develop the neighborhood level and make the neighborhood more resilient.

Nevertheless, the existing neighborhoods cannot be transformed to energy neutral neighborhoods on a yearly or monthly basis. Apart from the economic barriers such as required investments in the energy systems, transmission and distribution grids, some technological as well as operational barriers also could interrupt the developments. High penetration of PV panels mimicking the ‘duck curve’, upsetting the balance of the grids with excess generation during daytime and creating steep evening ramps is one of the technical problems that has been identified [97]. Installation of energy storage and controllable loads at different special levels, for instance, residential, neighborhood or city level could be a solution for these negative impacts of PV panels. However, further answers and remedies are still needed to overcome these barriers. All these technical, economic and environmental factors decelerate the realization of energy neutral neighborhoods.

Future perspective of this research is to analyze different case studies based on the aforementioned methodology to support decisions on clean energy initiatives at the neighborhood level.

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