Simulation-based design optimization of Local Energy Communities: a case study of the BAM living lab

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Abstract
The technical and economic benefits of local energy communities (LECs) are not always clear, which hinders the widespread adoption of LEC projects. Design support tools that can evaluate the potential performance of LECs could help to overcome this challenge. Therefore this study proposes a simulation-based design optimization approach that enables LEC designers to analyze the impact of different design decisions on the LEC performance. The proposed approach uses computational models for the electricity grid, photovoltaic systems, battery energy storage systems, and buildings to represent the LEC. The approach is demonstrated using a Dutch case study of several office buildings. The impact of different design variations is investigated on several performance indicators relevant to the LEC, among others the self-sufficiency of the LEC, the self-consumption, and the one-percent peak.

Highlights
- A simulation-based design optimization approach is proposed.
- It enables LEC designers to analyze the impact of different design decisions on LEC performance.
- Various models and model libraries that are used to represent the LEC are described.
- The approach is demonstrated in a Dutch case study of several office buildings.

Introduction
The local energy community (LEC) concept has gained popularity in recent years since it can support the energy transition in the built environment from using fossil energy to renewable energy. Several technical, economical, and social benefits of LEC can be distinguished (Manso-Burgos et al., 2022). For example, some of the technical benefits of a LEC are its potential to reduce local electricity peak loads and to alleviate congestion problems on the grid by locally matching demand and production. Economic benefits can be found in the reduction of the energy costs of the LEC members, e.g., by increasing the self-consumption of the community or by providing energy flexibility services to the grid operators. The social benefits of LECs are related to spreading knowledge and raising awareness about environmental issues among the members of the community.

Several LEC projects can be found (Brummer, 2018), but it is not widely adopted yet. This is caused by several reasons, e.g., due to regulatory barriers, but also because the technical and economical benefits are not always clear to the stakeholders. The latter could be alleviated with design support tools that are able to assess the expected potential of a LEC and can provide insights into the performance of various design options of the LEC.

This paper proposes a LEC design optimization approach that can be used by LEC designers for design support and to demonstrate the benefits of LECs to their clients. The proposed approach is based on computational models that represent LECs and their components including the electricity grid, photovoltaic systems (PVs), battery energy storage systems (BESS), and buildings. The design optimization approach is demonstrated for a Dutch case study of several office buildings (the BAM living lab) and investigates the impact of different design variations on the performance of the LEC.

The Python programming language (using libraries such as PandaPower and PVlib) and OpenModelica (using the Buildings library) are used in this study to model the LEC; OMPython is utilized to communicate between OpenModelica and the Python environment. This paper describes the various models and model libraries that are used to represent the LEC.

Modelling of local energy communities
One of the challenges in modeling LECs is the complexity of the system (Fodstad et al., 2022). LECs require the integration of various energy sources and technologies, such as PV and wind turbines, heat pumps (HPs), BESS, and electrical vehicles (EVs), among others. Furthermore, uncertain factors such as weather conditions and building occupant behavior can affect the energy demand and supply in the community. Therefore, models must account for the dynamic nature of these factors and their influence on the LEC. Another challenge is the lack of data required for accurate modeling. Data on energy consumption patterns, renewable resource availability, and energy prices can be difficult to obtain. This lack of data can limit the accuracy of the models. In this section, some background information on modeling LECs and their components is presented.

Modelling of BESS, EVs, and electrical networks
Typically, BESS and EVs can be modeled as (nonlinear or linear) equivalent circuit models, or electrochemical
models in terms of their state of charge (Schmalstieg et al., 2018). The electricity grid can be modeled in various ways depending on the purposes of system analyses. Electrical networks can be modeled as equivalent (multi-)port networks using network and port theory, or equivalent models using the Thevenin theorem (Mai et al., 2021; Naderi et al., 2018; Tran et al., 2022). The state-space model of a multi-bus electrical network can be developed through the linearization of equations describing components in the system, including power electronics-based converters, controllers, the electrical topology of the system described by nodal admittance matrix, and impedance-equivalent load models. These models can be used to evaluate system stability and performance, as well as components, and system-level controller designs.

The formulation of the physics-based mathematical models requires detailed knowledge of the actual system (including steady-state, dynamics behavior, and uncertainties), hence this approach might not also be applicable for components and LECs with complex structures. The integration of information and communication technologies, and advanced measurement infrastructure enables the development of data-driven approaches that can satisfy the growing demand for accurate, scalable LEC modeling. Accurate data-driven modeling approaches for PV are discussed in (Thomas & Nisar, 2015), in which the models are designed based on only representative sub-datasets from large input data, selected by a crucial pre-processing step. By doing so, the extremely large amount of unnecessary computation is reduced while the completeness and accuracy of the developed models are still guaranteed. Direct forecasting models for PV power generation can be developed using PV power output historical data samples as discussed by (Das et al., 2018). The EV charging stations can be represented by stochastic models, as proposed in (Y. Wang & Infield, 2018). These models also include uncertainties, such as charging classes, charging load profiles, and the location of the EVs. The high accuracy of these models allows various studies for grid-supporting services of these flexible resources.

Modelling of buildings in LEC

Building energy simulations can be applied on various temporal and spatial scales. Urban building energy modelling (UBEM) is used for larger spatial scales such as neighbourhoods or cities (Reinhart & Davila, 2016). In a previous work (Davila et al., 2016), the studies in the field of UBEM and bottom-up simulation methods and workflows have been reviewed. Furthermore, several reviews have been done on the modelling approaches and simulation tools for developing UBEMs (Ferrari et al., 2019; Frayssinet et al., 2018; Hong et al., 2020; Li et al., 2017; Sola et al., 2018). Some recent studies have used City Energy Analyst and MATLAB-Simulink to model and evaluate the performance of a positive energy district (Castillo-Calzadilla et al., 2021; Jepsen et al., 2022). In general, the used (building) models can be classified as white-box, grey-box, or black-box models depending on the input parameters (Andriamamonjy et al., 2019; De Coninck et al., 2016; Yang et al., 2018).

Proposed simulation framework

A design support tool for LECs can be used in various situations, e.g., when:

- developing a new LEC from an existing neighborhood or cluster of buildings;
- developing a new LEC from a new neighborhood or cluster of buildings;
- expanding an existing LEC by adding a building or a group of buildings.

The proposed approach in this research focuses on the first situation, i.e., information and data are available from the (existing) buildings in the new LEC. In this section, the details of the developed simulation framework for the LEC will be explained. The application of the proposed design optimization approach will be later demonstrated in the office reference case study.

Models of the LEC components

In order to develop a general simulation framework for investigating the performance of a LEC and the electricity grid, numerous requirements must be considered based on the assumed size of the LEC (T. A. Nguyen-Huu et al., 2022). Therefore, several assumptions are made: the LEC consists of 5 to 100 buildings/houses, with PV systems ranging from 100 kW to 300 kW, and flexible energy resources (FERs) like BESS, EVs, EV charging stations, and HP systems. The LEC is connected to the grid through a 22/0.4 kV transformer.

The LEC component models are developed using Python-based open-source tools, with the Pandapower solver being utilized for power flow calculations (Thunmer et al., 2018). The electrical element parameters, such as generators, power lines, loads, DERs, and FERs, are defined using a developed interface and stored in a table-type data structure. For instance, the “create_empty_network” function initializes the network model in the developed simulation framework. After creating the network, buses where all other elements connect to, and the lines connecting these buses, are added by using other functions from the library. The model of (either two or three winding) transformers can be assigned from the standard type library of Pandapower.

The PV model in the simulation framework is based on the open-source PVlib library and comprises a PV module that supplies DC power and a DC/AC inverter (Holmgren et al., 2018). The developed model can support both single- and multiple-array structures with array parameters inputted directly into the developed functions. The developed PV model allows the presentation of the input data (irradiance, ambient temperature, and air velocity), as well as the DC and AC power output of the PV system in both minute-based and hour-based time resolutions.

The BESS operation depends on the requirements of the LEC after estimating the maximum profit they can get based on the optimization algorithm (Li et al., 2020; T.-A. Nguyen-Huu et al., 2022). However, the BESS operation...
should satisfy some BESS constraints such as the state-of-charge limitations and life cycles of BESS.

Building energy models

A library of building models is developed using OpenModelica, an open-source Modelica-based modeling and simulation environment. The Buildings Library 8.1, a free open-source library for building and district energy and control systems, is also used. OMPython, a Python interface, is used to communicate with OpenModelica.

The developed library of building models consists of four reduced-order resistance-capacitance (RC) models with different complexity levels. An RC model describes a building based on an analogy with an electrical circuit, where electric resistances (Rs) and capacitances (Cs) represent the thermal R and C of building material layers. All the developed template models in this paper simplify the building structure into one thermal zone and use Rs and Cs to simulate its thermal behavior. To have a library of building models with different complexity levels, the number of Rs and Cs vary in the thermal zone of each model as follows:

- Model 1: 7 Rs and 2 Cs for the heat capacities of exterior walls and indoor air.
- Model 2: 11 Rs and 3 Cs for the heat capacities of exterior walls, interior walls, and indoor air.
- Model 3: 17 Rs and 4 Cs for the heat capacities of exterior walls, interior walls, floor, and indoor air.
- Model 4: 24 Rs and 5 Cs for the heat capacities of exterior walls, interior walls, floor, roof, and indoor air.

The energy and air flows are simulated in the models by implementing several Modelica-based sub-models connected to the RC thermal zone including weather data, internal gain, heat recovery system, heating and cooling system, and ventilation and infiltration.

To prevent errors or wrong specifications when developing a simplified building model, it is important to point out the uncertainties in the input parameters and identify the most influential ones on the simulation output (Hopfe & Hensen, 2011). This can be done by performing sensitivity and uncertainty analysis for the models (Hopfe & Hensen, 2011). Thus, a simple (one-at-a-time) sensitivity analysis is carried out in this study to understand the order of the most influential input parameters on the simulation outputs. For that, uncertainty ranges are defined for the uncertain input parameters. The impact of each parameter on the simulation output is investigated individually by setting them to the upper limit, lower limit, and middle values in the defined uncertainty range.

Once the most influential model parameters are identified, the values for these parameters need to be determined through a calibration procedure. In some recent studies (Devia et al., 2019; Z. Wang et al., 2019), a genetic algorithm (GA) is used to estimate input parameter values for RC models. In this paper also a GA is used for the same purpose. Minimizing the coefficient of variation of the root mean square error (CV(RMSE)) is used in the objective function for model calibration.

Case study description

The design optimization using the LEC simulation framework is demonstrated for a Dutch case study of several office buildings: the BAM living lab. The objective is to investigate the impact of different design variations on self-sufficiency (SS), self-consumption (SC), and one-percent peak (OPP). As shown in Figure 1, the living lab consists of 7 office buildings, located in Bunnik, the Netherlands.

![Figure 1: BAM living lab, located in Bunnik (NL).](https://doi.org/10.26868/25222708.2023.1453)

The buildings are insulated with Rc-values ranging from 1.7-2.8 for the walls and roof. The number of floors and value of WWR for all the buildings are 3 and 0.28, respectively. The total floor areas of all 7 buildings are reported in Table 1. All the buildings are currently equipped with gas boilers for heating with 90% efficiency, and there is no cooling system in the buildings. For model calibration, hourly gas data is converted to heating load using the lower heating value of natural gas (9.77 kWh/m³).

<table>
<thead>
<tr>
<th>The total floor area of each building [m²]</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total floor area of each building [m²]</td>
<td>3025</td>
<td>3707</td>
<td>1884</td>
<td>1284</td>
<td>2556</td>
<td>2652</td>
<td>4365</td>
</tr>
</tbody>
</table>

It should be noted that the internal gain is considered a constant value for all the occupancy hours from 7:00 to 18:00, and the value is obtained from a previous study (Nair, 2018). Furthermore, the heating and cooling setpoints for the occupied hours are set to 21°C and 23°C, and for unoccupied hours are set to 17°C and 28°C, respectively.

Design variations

The performance of two different design options related to the level of insulation in the building envelope, shown in Table 2, is evaluated on the LEC level. The first design option, DO2, represents the highest level of insulation considered in this study, which meets the current Dutch building standard. An intermediate insulation level between the reference values and the DO2 is also defined in this research (DO1). In model 2, the resistance values for walls and roofs are combined into one parameter. As
a result, the average value of Rc-wall and Rc-roof is used as the model input parameter for both design options, and it is labeled as Rc-external in Table 2. These design options are applied to all the buildings in the case study.

**Table 2: Considered building insulation packages.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Reference</th>
<th>DO1</th>
<th>DO2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rc-wall [m²k/W]</td>
<td>1.8 – 2.4</td>
<td>3.5</td>
<td>4.5</td>
</tr>
<tr>
<td>Rc-roof [m²k/W]</td>
<td>1.7 – 2.8</td>
<td>4.5</td>
<td>6.0</td>
</tr>
<tr>
<td>Rc-floor [m²k/W]</td>
<td>1.3 – 1.9</td>
<td>2.5</td>
<td>3.5</td>
</tr>
<tr>
<td>Rc-external [m²k/W]</td>
<td>1.7 – 2.8</td>
<td>4.0</td>
<td>5.25</td>
</tr>
</tbody>
</table>

Table 3 presents 24 design variations related to buildings, PVs, and BESS. The first dimension investigated three different sizes of PVs, including the original size (220kWp), twice the original size, and three times the original size. Another dimension is the building design options (thermal insulation and the HP), which results in three different design options: without HP (still using the gas boilers for heating), HP Ref., and HP DO2. For each dimension, the implementation with and without BESS is investigated to understand their impact on SS, SC, and OPP.

**Table 3: Considered design variations for the LEC.**

<table>
<thead>
<tr>
<th>Design variations</th>
<th>HP Design options</th>
<th>HP Design options</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV size factors</td>
<td>without HP</td>
<td>HP ref.</td>
</tr>
<tr>
<td></td>
<td>Implement HP</td>
<td>HP DO2</td>
</tr>
<tr>
<td>Original size x 1</td>
<td>Original size x 1</td>
<td>(50kW/1000kWh)</td>
</tr>
<tr>
<td>Original size x 2</td>
<td>Original size x 2</td>
<td></td>
</tr>
<tr>
<td>Original size x 3</td>
<td>Original size x 3</td>
<td></td>
</tr>
</tbody>
</table>

**Key Performance Indicators (KPIs)**

To evaluate the effectiveness of a BESS and other energy-saving measures, three key metrics are often used: SS, SC, and OPP. These metrics are commonly employed in the analysis of energy systems, particularly those that incorporate renewable energy sources.

SS is a measure of the proportion of energy consumed by an energy user that is generated on-site by renewable sources. The SS can range from 0% to 100%, with a higher value indicating a greater proportion of on-site energy production from renewable sources. The SS is calculated using the following equation:

\[
SS = \frac{\sum P_{used}}{\sum P_{demand}} \times 100\% = \frac{\sum P_{used}}{\sum P_{used} + \sum P_{exp}} \times 100\% \tag{1}
\]

Where \( \sum P_{used} \) is the total on-site energy production used locally, \( \sum P_{demand} \) is the total energy consumed on-site, and \( \sum P_{exp} \) is the energy imported from the grid.

SC metric is another important tool for analyzing the performance of an energy system that incorporates renewable energy sources. Unlike the SS metric, which measures the proportion of on-site energy production that is consumed on-site and from renewable sources, the SC metric measures the proportion of on-site energy production from renewable sources that are actually consumed on-site.

The SC metric ranges from 0% to 100%, with a higher value indicating a greater proportion of on-site energy production from renewable sources that is consumed on-site. The SC is calculated using the following equation:

\[
SC = \frac{\sum P_{used}}{\sum P_{total}} \times 100\% = \frac{\sum P_{used}}{\sum P_{used} + \sum P_{exp}} \times 100\% \tag{2}
\]

Where \( \sum P_{used} \) again is the total on-site energy production used locally, and \( \sum P_{total} \) is the total on-site energy production, \( \sum P_{exp} \) is the energy exported to the grid.

In order to maximize the SS and SC metrics, various optimization techniques can be employed to minimize the power exchange to the grid, which is represented by the sum of power imports and exports \( \sum P_{imp} + \sum P_{exp} \).

One effective way to achieve this optimization is by implementing an energy management system that controls the operation of a BESS and other energy-saving measures. The energy management system can be programmed to optimize the operation of the BESS, such as by charging the battery during times of excess on-site energy production and discharging the battery during periods of high energy demand.

In summary, the SS and SC metrics are useful for analyzing the performance of a battery and other energy-saving measures. Measuring the proportion of energy consumed on-site that is generated by renewable sources, provides valuable insights into the sustainability and efficiency of an energy system.

In addition, a LEC’s impact on the electricity grid can be minimized by reducing the absolute peak exchange power to the grid thanks to the optimized BESS operation (Mohammadi et al., 2020). In order to measure the net peak power exchange between the LEC and the grid, the OPP is used as a grid interaction indicator. This metric specifically focuses on the top 1% highest peaks in terms of absolute power exchange and provides the average value of the net power exchanged during those peaks.

OPP is calculated using the following equation:

\[
OPP = \frac{E1\%_{peak}}{\Delta t/100} \tag{3}
\]

Where \( E1\%_{peak} \) is defined as the exchange energy during the 1% highest peaks in exchange power, while the total considered time \( \Delta t \) represents the duration of the measurement period in hours.

**Building energy model calibration**

Four template RC models with varying complexities are developed. A simple (one-at-a-time) sensitivity analysis is performed as the first step in the calibration of the models. The calibration process is performed for the top six most influential parameters on the heating energy demand including ventilation rate, infiltration rate, heat recovery system efficiency, internal gain factor, g-value of the windows, and resistance of the external walls. The GA is used with a one-week training period in December 2021. The CV(RMSE) values of the testing period (from Dec 6th to Dec 10th, 2021) for all the buildings and all the model complexities, are shown in Table 4. Please note that buildings B and G could not be calibrated due to
incomplete data. Therefore, the thermal demand for these buildings was estimated based on the demand of other similar buildings in the case study.

Table 4: The CV(RMSE) value of different models for all the buildings in the BAM living lab.

<table>
<thead>
<tr>
<th>Building</th>
<th>CV(RMSE) of each complexity level (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
</tr>
<tr>
<td>A</td>
<td>25.1</td>
</tr>
<tr>
<td>C</td>
<td>29.8</td>
</tr>
<tr>
<td>D</td>
<td>32.8</td>
</tr>
<tr>
<td>E</td>
<td>28.5</td>
</tr>
<tr>
<td>F</td>
<td>28.3</td>
</tr>
</tbody>
</table>

The ASHRAE Guideline recommends a CV(RMSE) of <30% for hourly calibration. The results show that almost all models satisfy this requirement. During the testing period, the differences in CV(RMSE) values among the models show to be insignificant. After taking into account both the CV(RMSE) value and simulation time for each model, model 2 was selected as the optimal complexity level for the case study in this paper. It is important to note that this analysis did not consider uncertainty stemming from the conversion of gas meters to heating load.

As an example to demonstrate the performance of the developed building models for the case study, the hourly and monthly heating energy demand of Building A in comparison with the actual data is shown in Figure 2. The CV(RMSE) for monthly results (shown in Figure 2) is around 8%, which satisfies the requirements of the ASHRAE Guideline. Table 5 shows the difference between the yearly heating energy demand and the actual heating data of all the buildings, which ranges between around 2% for Building E and 9% for Building F.

Table 5: Predicted yearly heating energy demand and the yearly actual data for heating in 2021.

<table>
<thead>
<tr>
<th>Building</th>
<th>Predicted value [MWh]</th>
<th>Actual data [MWh]</th>
<th>Difference [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>175</td>
<td>181</td>
<td>3.3</td>
</tr>
<tr>
<td>B</td>
<td>110</td>
<td>118</td>
<td>6.7</td>
</tr>
<tr>
<td>D</td>
<td>61</td>
<td>missing data</td>
<td>N/A</td>
</tr>
<tr>
<td>E</td>
<td>184</td>
<td>181</td>
<td>1.6</td>
</tr>
<tr>
<td>F</td>
<td>214</td>
<td>236</td>
<td>9.3</td>
</tr>
</tbody>
</table>

Results

In this section, the developed simulation framework is applied to find answers to questions related to the design optimization of the buildings in the LEC, the size of PVs, and the benefits of BESS.

Performance of building design variations

The results of the total yearly heating and cooling electricity demand are demonstrated in Figure 3. It should be noted that the gas boilers in the reference case are assumed to be replaced with an HP with a COP of 3.0 (S. Wang et al., 2022). According to the results, the total yearly heating and cooling electricity demands of the buildings are decreased after applying the design options by approximately a range of 5% to 13% for DO1 and 7% to 15% for DO2. Due to the small difference between the yearly heating and cooling electricity demand of DO1 and DO2, only DO2 is considered for analysis of the LEC design variations in the next section.

Performance of BESS operation

Figure 3: The comparison between the yearly heating and cooling electricity demand of the reference buildings and different building design options.

Figures 4(a) and 4(b): (a) The power exchange from LEC to external grid, (b) The optimized BESS operation in April 2021.
Figure 4 shows an example of the load on the LEC when applying an optimal operational strategy for the BESS. The example shows the total load of the buildings, which is the sum of the original electricity demand of the buildings and the HP demand of the Reference case (see Figure 3) in April 2020: the load is illustrated by the cyan-blue dashed line in sub-Figure 4 (a). The size of the PV system in this example is two times the original size of the PV system; the electricity production is depicted by the orange dashed line. The BESS’s configuration comprises a 50kW/1000kWh capacity with a 6000-cycle lifetime, designed to support LEC in achieving maximum SC, SS, and OPP. The BESS charges or discharges within the SOC limitation range of [0.2, 0.8] to ensure their longevity as shown in Figure 4 (b). The charging/discharging cycles are kept to a minimum of one per day using an algorithm. Whenever LEC generates surplus power due to PV generation, the BESS charges this excess energy to reduce the power exported to the external grid, resulting in higher SC. In contrast, the BESS discharges power if possible when LEC obtains energy from the external grid, leading to higher SS. Figure 4 (a) portrays the exchanged power from LEC to the external grid, exhibited by the red line. Throughout April 2020, the exchange power remained lower than the net load (Majorelle blue line) of LEC, which facilitated higher SC, and SS through optimized BESS operation. In addition, in the morning, when the power demand is high due to HP operation, BESS discharges to alleviate the peak demand of the LEC, thus contributing to the achievement of an OPP indicator.

Performance comparison of LEC design variations

The present analysis focuses on the impact of BESS on the SC, SS, and OPP of LEC with PV and HP systems. Figure 5 depicts a comparison between the scenarios without and with BESS in terms of SC and SS during April 2021. Figure 5 (a) and (b) demonstrate the impact of BESS on SC. The results indicate that BESS increases LEC’s ability to consume more energy generated by PV systems compared to the scenario without BESS. Furthermore, a proportional relationship is observed between the size of the PV and the increase in SC due to the installation of BESS. Specifically, the SC rate increases from about 8% to 15% and 18% with a two-fold and three-fold increase in the size of the PV, respectively. Figure 5 (c) and (d) display the impact of BESS on SS. The analysis reveals that the energy stored in the BESS after charging from the surplus power generated by the PV system supports LEC to become more SS. The results show an approximately 10% increase in SS in the scenario with BESS compared to that without BESS for the original size of PV systems. Moreover, with a two-fold or three-fold increase in the size of the PV, the SS rate increases by approximately 15%. Additionally, the analysis indicates that the SS of LEC increases with the increase in the size of the PV system.

The impact of HP design options on the SC and SS LEC is also presented in Figure 5. The analysis reveals that, in general, the original electricity load without any HP systems provides greater SS for LEC than installing HP systems. However, LEC incurs higher costs for gas consumption to heat their building, which is higher than their electricity bill. Therefore, HP systems should be considered to support LEC’s utility bill. Furthermore, the results indicate that after applying different building insulation packages, LEC achieves higher levels of SC and SS. Nevertheless, due to the short period of investigation, the improvement in supporting LEC’s bill is limited.

The impact of BESS on OPP is illustrated in Figure 5 (e) and (f). Overall, BESS operation has been found to mitigate the peak demand or peak surplus power to the network, resulting in a lower OPP in the scenarios with BESS as compared to the ones without BESS. In the absence of an HP system, the BESS charges surplus power due to the high penetration of PV systems. This leads to a reduction in the OPP when the size of the PV system is increased two-fold or three-fold. Conversely, in the presence of HP, the BESS discharges in the morning to mitigate the high peak demand caused by HP operation.

There is no significant difference between HP ref. and HP DO2 in terms of OPP because the BESS operates within the network constraints to avoid transformer loading violations.

**Conclusion**

Design support tools are necessary to evaluate the technical and economic potential of LECs. This study proposes a simulation-based design optimization...
approach that enables LEC designers to analyze the impact of different design decisions on LEC performance. The approach is demonstrated in a Dutch case study of several office buildings. The performance of several design variations is investigated.

**Practical application of the proposed approach**

The findings of this study indicate that the developed approach can answer LEC design questions related to the building insulation level and PV sizes. The approach is also capable of investigating the benefits of adding a BESS to the LEC. In addition, it provides the possibility of testing and using different complexity levels for models of different buildings in the LEC. The results of the case study also underline the successful application of the proposed approach.

**Limitations and future work**

The proposed design optimization approach is limited to cases where data and information are available from existing buildings in the new LEC. Future research will explore cases with limited or no data availability. Furthermore, future uncertainties related to climate scenarios, grid decarbonization, energy mix scenarios, and price scenarios are not taken into account in the proposed approach. Therefore, future work intends to perform scenario analysis to make robust decisions for LECs.

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**References**


Electric Power Systems Research, 192.


Nguyen-Huu, T.-A., Tran, T. T., Nguyen, P. H., & Slootweg, J. G. (2022). Network-aware operational strategies to provide (flexibility) services from Local Energy Community; Network-aware operational strategies to provide (flexibility) services from Local Energy Community. 2022 57th International Universities Power Engineering Conference (UPEC).


